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Department of Environmental Engineering

PhD Thesis
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Preface

The work presented in this PhD thesis was conducted at the Department of Environmental Engineering (DTU Environment) of the Technical University of Denmark (DTU) from January 2009 to January 2014. The supervisor team consisted of Professor Peter Steen Mikkelsen (DTU Environment), Dr Morten Grum (Krüger A/S, Veolia Water Solutions and Technologies) and Professor Henrik Madsen (DHI). The PhD project was part of the Storm and Wastewater Informatics (SWI) project (http://www.swi.env.dtu.dk) and was financially supported by the Danish Council for Strategic Research, Programme Commission on Sustainable Energy and Environment, the Technical University of Denmark and the utility companies HOFOR, Lynettefællesskabet, Spildevandscenter Avedøre and Aarhus Vand.

This thesis is based on six scientific papers of which one is a manuscipt while the rest have been published or submitted to international conferences or journals. The Papers are referred to by their roman number throughout this thesis (e.g.: **Paper I**). The numbering has been done according to the research aims formulated in the introduction.

Papers included in this thesis:

I. **Borup, M.,** Grum, M., Mikkelsen, P.S., 2013. Comparing the impact of time displaced and biased precipitation estimates for online updated urban runoff models. *Water Science and Technology* **68** (1), 109–116.

II. **Borup, M.**, Grum, M., Linde, J.J., Mikkelsen, P.S., 2009. Application of high resolution x-band radar data for urban runoff modelling: constant vs. dynamic calibration, in: *Proceedings of 8th International Workshop on Precipitation in Urban* Areas, 10-13 December, 2009, St. Moritz, Switzerland. 27–31.

III. **Borup, M.**, Grum, M., Mikkelsen, P.S., 2011. Real time adjustment of slow changing flow components in distributed urban runoff models, in: *Proceedings of the 12th International Conference on Urban Drainage*. Porto Alegre/Brazil, 11-16 September 2011. Full paper PAP005261. 8 p.

IV. Hansen, L.S., **Borup, M.**, Møller, A., Mikkelsen, P.S., 2011. Flow Forecasting using Deterministic Updating of Water Levels in Distributed Hydrodynamic Urban Drainage Models. (Manuscript).

V. **Borup, M.**, Grum, M., Madsen, H., Mikkelsen, P.S., Updating distributed, physically-based urban drainage models using the Ensemble Kalman Filter. (Manuscript).

VI. **Borup, M.**, Grum, M., Madsen, H., Mikkelsen, P.S., A Partial Ensemble Kalman Filtering approach to enable use of range limited observations. (In revision).

In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from: DTU Environment, Technical University of Denmark, Miljoevej, Building 113, 2800 Kgs. Lyngby, Denmark, reception@env.dtu.dk.

The following articles were also prepared during this PhD project but are not included in the thesis:

Borup, M., Grum, M., Mikkelsen, P.S., 2012. Impact of time displaced precipitation estimates for online updated model. in *Proceedings of the 9th International Conference on Urban Drainage Modelling*, Belgrade/Serbia, 4-6 September 2012. Full paper, 1-10.

Hansen, L.S., **Borup, M.**, Møller, A., Mikkelsen, P.S., 2011. Flow Forecasting in Urban Drainage Systems using Deterministic Updating of Water Levels in Distributed Hydraulic Models. in *Proceedings of the 12th International Conference on Urban Drainage*. Porto Alegre/Brazil, 11-16 September 2011. Full paper PAP005261. 1-8.

Plósz, B.G., Reid, M.J., **Borup, M**., Langford, K.H., Thomas, K. V, 2013. Biotransformation kinetics and sorption of cocaine and its metabolites and the factors influencing their estimation in wastewater. *Water Research* **47**(7), 2129–2140.

Thorndahl, S., Poulsen, T.S., Bøvith, T., **Borup, M**., Ahm, M., Nielsen, J.E., Grum, M., Rasmussen, M.R., Gill, R., Mikkelsen, P.S., 2013. Comparison of short-term rainfall forecasts for model-based flow prediction in urban drainage systems. *Water Science and Technology* **68**(2), 472–478.

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The PhD project is a part of the Storm and Wastewater Informatics (SWI) project (http://www.swi.env.dtu.dk). The SWI project was financially supported by *the Danish Council for Strategic Research, Programme Commission on Sustainable Energy and Environment* as well as the following partners:

- Technical University of Denmark (DTU)
- Aalborg University (AAU)
- Danish Meteorological Institute (DMI)
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- Krüger A/S
- Avedøre Wastewater Services
- Hovedstadsområdets Forsyningsselskab (HOFOR)
- Lynettefællesskabet
- Aarhus Water

I thank all partners and colleagues in SWI for the valuable collaborations in the project. Furthermore the Urban Water Technology Research School, in which I have been enrolled, is acknowledged.

I would also like to thank Vandcenter Syd and Annette Brink-Kjær for access to radar, raingauge and water level data for my radar experiments, as well as my former Colleagues at Krüger A/S for assistance with modelling expertise.

I will also give a special thanks to Jesper Grooss from DHI for the fast and invaluable help with getting access to the internals of the computational engine of Mike Urban. I sent him an email late one Saturday with an urgent request for the implementation of a specific feature in the computational engine, and he responded the very same evening with an email with a recompiled version of the engine with that feature implemented. I will furthermore like to thank Marc-Etienne Ridler at DHI for letting me use the DA framework he is developing for DHI as basis for my experiments with Mike Urban.

Also a big thanks to all my colleagues at DTU Environment. Especially to Anne Harsting who made sure that I did not have to worry too much about the administrative stuff.

Finally I would like to thank my wife and kids for putting up with my absence in some of the busy periods of the project.

Summary

When it rains on urban areas the rainfall runoff is transported out of the city via the drainage system. Frequently, the drainage system cannot handle all the rain water, which results in problems like flooding or overflows into natural water bodies. To reduce these problems the systems are equipped with basins and automated structures that allow for a large degree of control of the systems, but in order to do this optimally it is required to know what is happening throughout the system. For this task models are needed, due to the large scale and complex nature of the systems. The physically based, distributed urban drainage models (DUDMs) are the most detailed models available of the urban drainage system. They contain a virtual replica of the main parts of the hydraulic system and can therefore potentially be used to estimate the hydraulic conditions anywhere in the system.

In order to produce useful estimates of the conditions in the system the models are highly dependent on the rainfall data used as model forcing. The rainfall estimates from raingauges as well as weather radar are, however, very uncertain for the spatial and temporal scale required for urban runoff simulations. This is especially so for the convective events of the summer. Therefore a method was developed for adjusting radar rainfall estimates using raingauge measurements in areas with an existing dense network of raingauges. The result was much improved rainfall estimates, which proved good enough to allow quantitative overflow modelling.

As with raingauge data the acquisition of online radar data is an economic expense and therefore it is necessary to be able to prioritise whether to invest in one or the other. In a theoretical study the impact of choosing one type of rainfall data over the other for models that are being updated from system measurements was studied. The results showed that the fact alone that it takes time for rainfall data to travel the distance between gauges and catchments has such a big negative effect on the forecast skill of updated models, that it can justify the choice of even very uncertain radar data over raingauge data.

Rainfall estimates will never be perfect and nor will the models. Therefore model estimates will continue to be uncertain. The uncertainty within the models can be reduced by means of data assimilation (DA) that correct the models based on comparisons between model estimates and system observations. The only current existing operational DA method for DUDMs is the Mouse Update tool, which works by correcting the water levels locally in the model at the observed sites. In

a case study this simple DA tool proved to have some ability to improve downstream flow forecasts when it was used to update the water level in multiple upstream basins. This method is, however, not capable of utilising the spatial correlations in the errors to correct larger parts of the models. To accommodate this a method was developed for correcting the slow changing inflows to urban drainage systems that relate to infiltrating water. The method works by estimating a linearised version of the model response, which is used to control the correction by the DA scheme in such a way that model stability is ensured without dampening the correction more than necessary. A case study showed that this method can significantly improve a DUDMs forecast ability when a large part of the runoff from a catchment comes from infiltrating water. The proposed method is computationally efficient since it does not require additional model simulations. The method is, however, limited to adjusting the inflow to the hydrodynamic model and is not capable of updating the water levels in pipes and basins explicitly.

The statistical data assimilation method the *Ensemble Kalman Filter* (EnKF) was investigated as a tool to update all the state variables in a DUDM. The method was tested in synthetic experiments as well as in a real data case study. The results confirmed that the method is indeed suitable for DUDMs and that it can be used to utilise upstream as well as downstream water level and flow observations to improve model estimates and forecasts.

Due to upper and lower sensor limits many sensors in urban drainage systems (and elsewhere) do not measure the quantity they are observing continuously. A new method was developed for utilising this kind of range-limited observations better when using the EnKF. The method works by counteracting the ensemble in spreading into to observable range when the lack of observations indicate that the quantity is outside this range. Synthetic experiments using a linear reservoir cascade model showed that the method can significantly improve model forecasts when observations frequently are outside the observable range. An experiment with a simplified DUDM showed that the method is suitable for assimilating range-limited water level observations from an overflow structure.

This thesis contributes some important stepping stones towards the online usage of physically based, distributed urban drainage models for both estimation and forecasting purposes. Provided that a good model exists for an urban area with weather radar data coverage, the principles are now outlined for synthesising most of the data from the system into an online model.

Dansk sammenfatning

Når det regner over byer kan det resultere i såvel oversvømmelser af kældre og veje som overløb fra afløbssystemet, hvilket kan forurene nærliggende vandløb og badevand. For at reducere disse problemer er afløbssystemerne udstyret med bassiner og diverse aktuatorer der muliggør en vid udstrækning af kontrol med systemerne. For at kunne kontrollere systemerne bedst muligt er det i imidlertid nødvendigt at vide hvad der foregår, og til dette er det nødvendigt at bruge modeller pga. størrelsen og kompleksiteten af systemerne. De fysisk baserede, distribuerede afløbsmodeller (DUDM) er de mest detaljerede modeller af afløbssystemet der findes. De kan indeholde et virtuelt replika af hele det hydrauliske system, inklusiv hvert eneste rør og konstruktion, og kan derfor potentielt bruges til at estimere vandføring og niveau overalt i systemet.

Modellernes muligheder for at lave brugbare estimater er meget afhængige af kvaliteten af de regndata der bruges som input. Imidlertid er regn-estimaterne fra både regnmålere og vejrradar meget usikre for den spatielle og temporale skala der er brug for, når man modellerer regnafstrømning fra byer. Det er specielt tilfældet for konvektiv sommer regn. Derfor blev der udviklet en metode til realtidsjustering af radar regn-estimater ved hjælp af regnmålerdata for områder hvor der er mange regnmålere. Dette resulterede i væsentligt forbedrede regn-estimater, der viste sig gode nok til at lave kvantitativ overløbsmodellering.

At anskaffe regndata fra såvel regnmålere som vejrradar er en økonomisk udgift og derfor er det vigtigt at kunne sammenligne konsekvenserne af brugen af de to typer nedbørsdata. I et rent teoretisk studie blev det vist at kravene til nedbørsdata ændrer sig, når modellerne bliver opdateret ved hjælp af målinger fra systemet. Resultaterne viste at alene det faktum at det tager tid for et regnområde at bevæge sig fra en regnmåler til et givent opland gør at nedbørsestimaterne fra vejrradar kan være af væsentligt lavere kvalitet end regnmålerdata og stadig være det bedste valg for online opdaterede modeller.

Regn-estimater og modeller vil aldrig blive perfekte og derfor vil model estimater altid være behæftet med usikkerhed. For at reducere model usikkerheden kan man bruge data assimilering (DA), der er matematiske værktøjer til at korrigere modellen ud fra sammenligninger mellem modellerede værdier og målte værdier fra systemet. Det eneste eksisterende operationelle DA værktøj for DUDMs er Mouse Update. Dette fungerer ved at korrigere vand niveauerne i modellen de steder hvor der er observationer til rådighed. Denne simple DA metode blev testet i et case studie, og den viste sig at være i stand til at forbedre afstrømningsforudsigelser når der blev opdateret i mange opstrøms bassiner. Metoden er imidlertid ikke i stand til at fordele korrektionerne ud over modellen, og udnytter dermed ikke de korrelationer der måtte være i systemet. Når der er meget indsivning i et opland vil der være en høj grad af korrelation imellem opstrøms og nedstrøms vandføring. For at udnytte dette i en DA sammenhæng blev der udviklet en metode til at opdatere modeller for oplande med megen infiltration. Kernen i metoden går ud på at estimere en lineariseret version af modellens respons, hvilket efterfølgende bruges til at dæmpe korrektionerne til modellens infiltrationsmodul på en sådan måde, at den opdaterede model reagerer så hurtigt som muligt på forskelle mellem måling og model, uden at modellen bliver ustabil. I et case studie blev det vist at metoden kan forbedre forecast egenskaberne af modeller betydeligt for oplande hvor infiltration står for en betydelig del af afstrømningen. Metoden har den fordel at den er meget beregningsmæssigt effektiv, da den ikke kræver ekstra model simuleringer. Til gengæld er den begrænset til at opdatere tilstrømningen til det hydrauliske netværk og kan således ikke direkte opdatere niveauer i ledninger og bassiner.

Den ensemble baserede DA metode *the Ensemble Kalman Filter* (EnKF) blev testet som et værktøj til at opdatere niveauer i modellerne. Metoden blev testet i såvel syntetiske setups som på rigtige målte data. Resultaterne viste at metoden kan bruges til at opdatere modellerne fra både nedstrøms niveau og vandføringsmålinger såvel som opstrøms niveau målinger.

Mange målere i afløbssystemer har øvre og/eller nedre målegrænser. Når disse målere ikke måler noget siger det derfor ikke noget om det absolutte niveau af det de observerer, men det siger noget om hvilke værdier det observerede ikke antager. En metode blev udviklet der muliggør at inkludere denne type information i EnKF opdatering. Test viste at metoden kan forbedre afstrømningsforudsigelser betydeligt og desuden kan bruges i forbindelse med niveau målinger fra overløbsbygværker.

Denne afhandling indeholder betydelige bidrag på vejen mod at kunne bruge de fysisk baserede, distribuerede afløbsmodeller som online modeller. Såfremt der er adgang til en god model og radar data er til rådighed, er det nu muligt at kombinere informationen fra en stor del af de målere der er til rådighed i afløbssystemerne i modellen.

Contents

1. Introduction

1.1 Offline and online urban runoff modelling

Urban drainage systems represent the third most expensive asset in the Danish society (FRI, 2008), surpassed only by buildings and roads. In order to exploit this huge investment to its maximum potential, it is important to understand what is happening in the system so that the system can be operated and maintained in an optimal way. Models are needed to conduct this task due to the scale and complexity of the systems. Various types of urban runoff models exist, reflecting the various purposes for which they are used. The complexity of these models spans from very simple relationships between flow and retention-time used for water quality modelling, cascades of linear reservoirs used for flow forecasting, and to the very detailed, physically-based distributed urban drainage models (DUDMs) that simulate the runoff from urban areas in great detail, from when the rain hits the surface until it leaves the drainage system. The latter models were originally developed to assist in the planning, design and analysis of drainage systems and are heavy to run computationally. With the continuous development in computer efficiency, however, it is becoming possible to use these models online. This potentially allows for producing better downstream flow forecasts, forecasting overflows and local flooding, detailed tracking of pollutants as well as model-based quality control of system gauges. All of this can be used to improve real time control and decision making as well as issue warnings and estimate pollutant loads.

1.2 Reducing uncertainties in online models

Before models are used for decision-making, uncertainties in model estimates should be reduced as much as possible with the information available. The main source of uncertainty in urban runoff modelling is rainfall estimates used for model forcing. Therefore, a natural starting point for reducing uncertainty is to acknowledge the uncertainties related to the specific rainfall estimates, and then try to minimise these accordingly. Neither rainfall estimates nor models are ever going to be perfect, however, so any online model needs to be adapted to current system conditions by assimilating in-situ observations into the model. In so doing, the model is used to combine multiple data sources, where each data source added contributes to lowering the model uncertainty.

Numerous data assimilation (DA) schemes exist for performing this kind of task, but very limited information is found in the literature on this subject in relation to

DUDMs. An optimal DA scheme performs subsequent estimations of the model's error statistics while updating its variables, in order to determine how much the model should be trusted compared to observations. This kind of DA is called 'statistical DA' in the following sections. The contrasting methods are 'deterministic' DA, which only estimates the model variables based on some prior assumptions regarding the size and distribution of the errors. The benefit of the deterministic approach is that it has much lower computational costs.

Urban hydraulic and hydrological systems differ fundamentally from other hydrological systems in three distinct ways, each of which has a significant influence on data assimilation. First of all, most of the flow happens in closed pipes, which means that the hydraulic response of the system can vary dramatically according to the state of the system. Secondly, the many impervious surfaces result in a very rapid response to rainfall, which means that the short-term uncertainty of rain measurements is transferred directly to the model. Finally, the use of real-time control results in instantaneously changing system behaviour following an operator's choice of control scheme. These reasons, combined with the computational costs of running a DUDM, might be why DUDMs have not yet found widespread popularity as online models.

1.3 Key research aims

The aim of this thesis is to explore ways to reduce uncertainty in online urban rainfall runoff modelling. The main focus is on DUDMs, and the main aim is to move closer to being able to use these models online, in order to synthesise all potentially available data from the urban drainage system.

The following subjects are investigated in this thesis:

Rain data for online models:

- Comparing the impact of the very different types of rainfall estimation errors from radar data and raingauge data on updated runoff models, in order to assess which is the most suited type of model forcing for updated urban runoff models (**Paper I**).
- Investigating whether the accuracy of radar rainfall estimates can be improved by adjusting them to raingauge observations to the extent where they are good enough to enable online quantitative overflow simulation (**Paper II**).

Deterministic updating of DUDMs:

- Investigating the performance of the existing deterministic DA tool "Mouse Update" for updating water levels in basins (**Paper III**).
- Developing a deterministic DA method for updating the model variables governing infiltrating inflow (**Paper IV**).

Ensemble based statistical DA for DUDMs:

- Investigating and testing whether ensemble-based DA schemes are suitable for DUDMs (**Paper V**).
- Developing a method for assimilating observations with a limited range, since many gauges in urban drainage systems have an upper or lower detection limit **(Paper VI)**.

1.4 Outline

Chapter 2 introduces the physical system and processes governing urban runoff, as well as the observations usually available from these systems. This is followed by Chapter 3, which introduces the concept of data assimilation and some of the most important data assimilation methods. Chapter 4 discusses the various sources of rainfall data available as well as the impact of the choice of rainfall input for an updated runoff model (**Papers l + II**). Chapter 5 investigates options for deterministic DA for DUDMs (**Papers III + IV**) while Chapter 6 describes how a DUDM can be updated using the Ensemble Kalman Filter (EnKF) (**Paper V + VI**). The two last chapters are *Conclusions* and *Potential for further research*, respectively.

2. Urban runoff: processes, system, observations and models

2.1 Runoff-generating processes

Urban runoff in this thesis applies to all water that runs out of an urban area. The part of the runoff that plays the biggest part in the current work is rainfall-dependent runoff, since this is the most challenging to handle for the drainage systems and models. In addition is actual wastewater flow that results from urban water consumption, but this is usually insignificant in size compared to peak rainfall runoff. Wastewater carries the bulk of pollutants, and it is therefore very important to consider when examining pollutant fluxes; however, since the current work focuses on hydrodynamics, wastewater flow is only touched upon briefly.

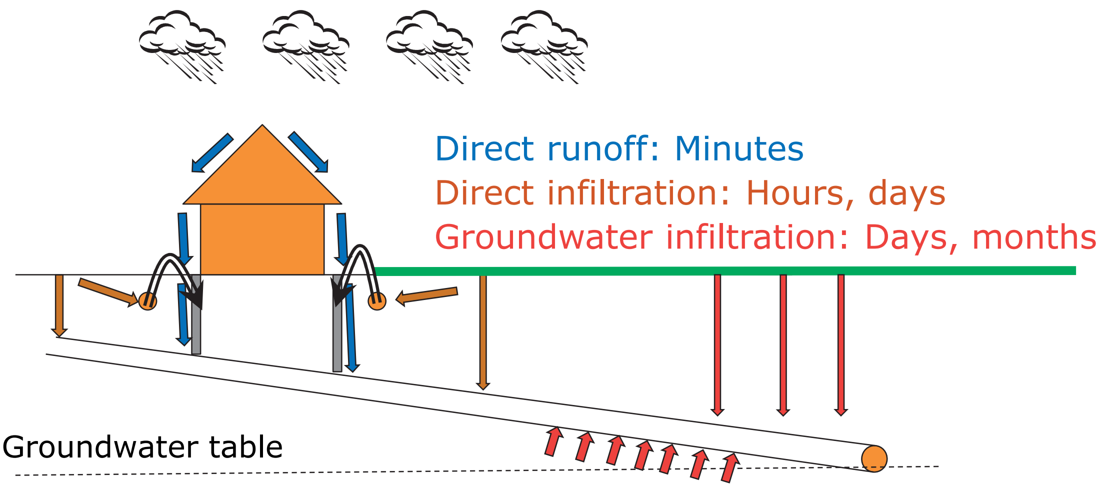

Figure 1: Timescales for runoff-generating processes.

The processes that lead to rainwater entering drainage systems can conceptually be divided into three main components, each of which is governed by different timescales (see **Figure 1**):

- **Direct runoff**: Rain that hits impervious surfaces, such as roofs and roads, and runs to the drainage system within minutes. This is usually the part of the runoff that dominates peak flows during rain events.
- **Direct infiltration**: Rain that hits pervious surfaces and percolates down through the soil directly into the pipe system or is caught by perimeter drains around buildings and then pumped into the drainage system. The timescale for

this process is hours or days, and it often determines the receding tail in the hydrograph seen after a rain event.

- **Groundwater infiltration**: Rain that ends up percolating down through the ground and raises the groundwater table to an extent where it can infiltrate into the pipe system. The timescale for changing groundwater levels is days or months, and it can explain varying dry weather flow throughout the year.

2.2 Hydraulic system

From a distance, the branched nature of an urban drainage system closely reassembles that of a natural river network, see **Figure 2**. There are some very important differences in the hydraulic response of the systems, however, arising from the fact that most of the flow in an urban drainage network runs through closed pipes.

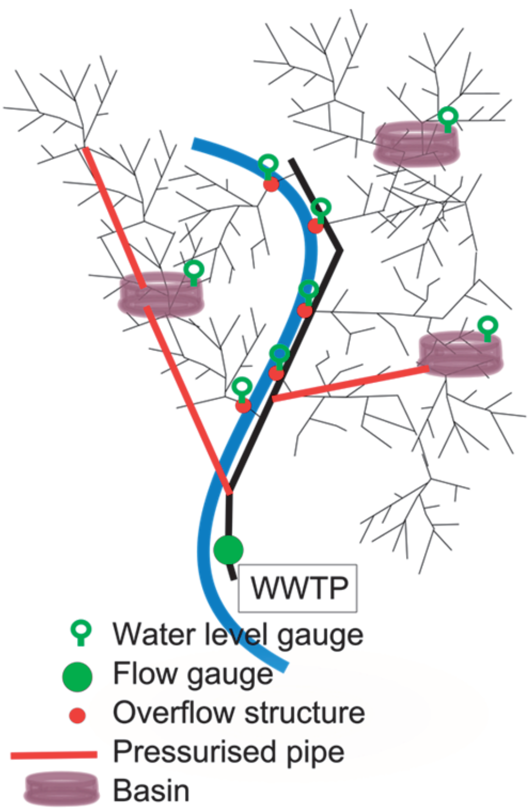

Figure 2: Sketch of an urban drainage system with basins, overflow structures and pressurised pipes.

When the pipes are only partially filled, any change in the inflow of water into a pipe stretch will simply result in a change in the water level in the pipe and, dependent on the flow conditions, the mean flow velocity. Once the pipe is full, the cross-sectional area of the flow cannot be increased, thus meaning that the only way to increase flow through the pipe is to increase the velocity. As a result, shear stress, and thus the difference in the hydraulic head along the pipe, grows rapidly with the flow. This is illustrated in **Figure 3** (left), where the simulated steady state relationship between flow through a pipe section and water depth in the nodes is plotted. Until the pipes run full with a flow of approximately 2.2 m3/s, water depths in the manholes remain almost exactly the same; however, if the flow is increased to 3 m3/s, there is a difference in water depth from the first to the last manhole of 7 metres. Consequently, there is an effective upper limit to the flow through a pipe. When the flow starts to rise above the pipe capacity, water will back up in the pipe system (as well as basements and surface depressions) and wait for excess capacity, find another route through the often highly interconnected systems or disappear out of the system through an overflow structure.

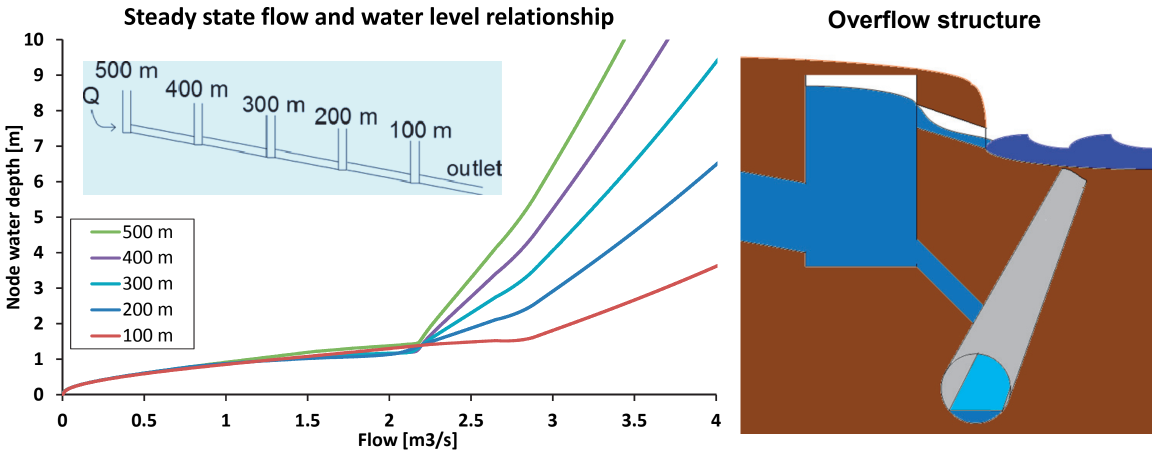

Figure 3: (Left) Steady state relationship, simulated with Mike Urban, between the flow Q and water depth for five manholes in a 500 m pipe stretch with a free downstream outlet. All pipe diameters are 1 m. (Right) Illustration of an overflow structure in action.

2.2.1 Overflow structures

Overflow structures are important 'safety valves' for urban drainage systems used to control where the water will exit the system when this is overloaded (see **Figure 3**, right). An overflow structure is usually constructed with a relatively long weir over which the water flows when the level exceeds the crest of the weir. Making the weir long ensures that the water level cannot go very much above the crest level and thus protects e.g. upstream basements from flooding. Overflow structures are very important for data assimilation for several reasons. First of all, overflows can make system responses very non-linear, since excess water simply disappears from the system. Secondly, overflow structures are often equipped with gauges to register overflows and lastly, the minimisation of overflow is often a priority and therefore something that is relevant to be able to model and forecast.

2.2.2 Basins

Basins are part of any urban drainage system in order to give the system an extra capacity to be used during rain. Some basins are used purely to even out the flow peaks while others are used to withhold large volumes of water in order to avoid flooding or reduce overflow. Larger basins are often emptied by pumping and both the pumping and the inflow to the basin can often be controlled centrally. When the basin volume in a catchment is large the basins can significantly affect the system behaviour, and they are therefore interesting from a DA point of view. They are furthermore often equipped with water level sensors.

2.2.3 Pumps and pressurised pipes

Pumping large amounts of water through pressurised pipes over long distances is another frequently occurring element of urban drainage systems. Since these pipes are always filled with water, there is an immediate response at the receiving end of the pipe when pumping begins. As a result, the flow from one area is transferred immediately to a completely different location in the system, thus creating some very strong, long-range correlations within the system.

2.2.4 Ever-changing system behaviour

Many mechanical structures in urban drainage systems can react autonomously in relation to local conditions and temporally change system behaviour. A common example of this point is non-return valves, which are pushed open by water when the pressure drop is sufficiently large over the valve. Another example is bendable weirs, which are pushed open once the water level in an overflow structure is above a certain threshold and then stay open until the water level has fallen below some lower threshold. This means that once an overflow has started, water will flow out of the system at water levels that would not have caused overflows in the first instance.

Real time control (RTC) is often used to control the filling and emptying of basins and the status of gates, pumps, etc. based on observations in the system. The water level in one basin, for instance, can be used to control whether water should be lead to a basin in a completely different part of the system. Besides creating long-range correlations in the hydraulic conditions within the system, RTC also makes system behaviour more complex and varied over time, since RTC schemes are changed easily and are prone to be so due to frequent system optimisations.

2.3 Observations

Figure 2 shows where water level or flow gauges are usually found in an urban drainage system. Water level sensors will usually be found in any major overflow structure or basin. Flow gauges are vulnerable and expensive and are therefore often only placed at the inlet to the wastewater treatment plant (WWTP). Just a few years ago, information from various gauges in the system was only collected centrally at rather low frequencies, such as once every hour, day or even month. Today, most gauges either are, or are on the way to becoming, accessible online. As an illustration, the utility company HOFOR that governs most of the Copenhagen area's urban drainage system has 270 online water level gauges and approximately 50 sites with flow gauges (Mollerup, 2013).

2.3.1 Water level gauges

Water level gauges are the cheapest, most reliable and most frequently occurring types of gauges. Typical water level gauge observation uncertainty when the gauge is working properly is less than 1% (Campisano et al., 2013). One of the most frequently used water level gauges is the pressure transducer (Benedetti et al., 2013), which can only measure water depth when submerged. In order to reduce maintenance costs, they are usually placed higher than the dry weather water levels. An example of data from such a gauge situated in an overflow structure can be seen in **Figure 4**. The gauge has a lower detection limit at 6.7 m, and it only observes actual water depth during rain events when the water level in the structure is higher than normal. The modelled results show how much the water level can actually vary. The missing peak in the modelled water level is caused by the raingauge data used as model forcing, which completely missed a peak in the rainfall.

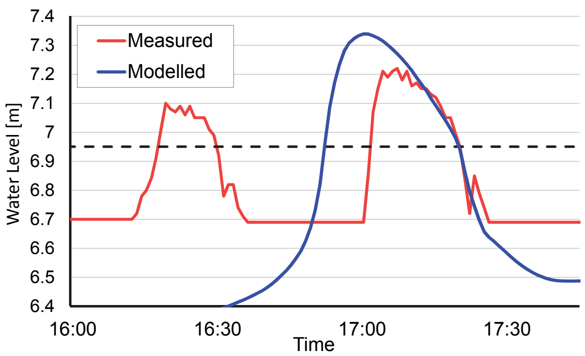

Figure 4: Data from a pressure-based water level gauge situated in an overflow structure at level 6.7 m. The blue line is simulated water level for the same location using a Mike Urban model forced by a nearby raingauge and the dashed black line indicates the crest level.

2.3.2 Flow gauges

All flow observations depend on water level observations. The most precise flow observations are made by converting the observed water level at a specially designed weir into flow. However, this is a very expensive way to measure flow and is not practically possible in many places in urban drainage systems, because it introduces a flow constraint. Therefore, actual flow gauges situated in the systems are usually a combination of a water level gauge and some sort of velocity sensor. The water level is then used to compute the wetted cross-sectional area of the flow, which enables for the flow rate to be calculated by multiplying the area with the measured flow velocity. This means that the computed flow is affected by errors made by both the water level gauge and the velocity sensor. Gauges in urban drainage systems reside in very harsh environments and therefore often have very bad or unpredictable performance, which ultimately makes it hard to quantify observation errors. An example of a time series of 5 minute flow measurements can be seen in **Figure 5**. Note that the measured flow is not particularly noisy from step to step but that there are a few very large sudden changes in the flow rate at 04:00 to 07:00 that do not look realistic. It is impossible to determine from the data series alone whether the observed values are correct or if the high or low interpretations of the data shown on **Figure 5** (right) are correct. Further similar examples can be found in (Brødbæk, 2013). The kind of error that is shown in the figure is not easily quantified and the magnitude of errors for urban drainage flow gauges can be quite high. For instance, Bertrand-Krajewski et al. (2003) found relative errors of 20% in measured flow rates in sewer pipes, despite carefully controlled experimental conditions.

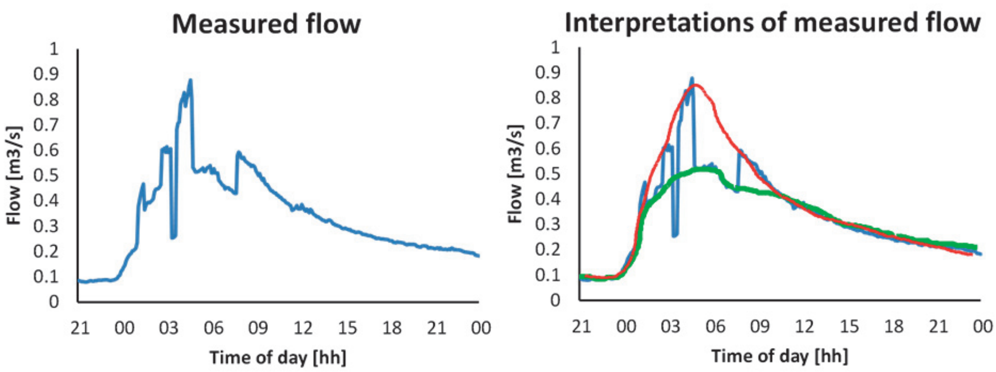

Figure 5: (Left) Flow measurement during a rain event. (Right) Two likely interpretations of the data.

2.3.3 Indirect observations

Water levels and flow gauges only provide a fraction of the information collected throughout the drainage system. The most abundant source of information will in many systems be power consumption in pumping stations. This data can be converted into an approximate flow or into information about the minimum or maximum water levels in the pump sump. The status of bendable weirs and non-return valves also provides information about local water levels. The observation uncertainties for many of these indirect observations are hard to quantify and changes over time. If, for instance, a pump controlled by the water level in a pump sump has not used electricity for a while, it provides the information that the water level is below the threshold for starting the pump but nothing about the absolute level. The moment the pump starts the water level is known with a small uncertainty but from that time and until the pump stops the electricity consumption only provides the information that the water level is above the lower threshold for stopping the pump. Estimation of flow rates from electricity consumption is more uncertain in the start-up and stopping periods of the pumping than once the pump reaches its maximum capacity.

2.4 Urban runoff models

Many different kinds of models are used for modelling urban runoff, depending on the purpose of the model. All models are in fact simplifications and the choice of model is often based on the required level of complexity. In urban runoff modelling the complexity ranges from very simple models of the hydraulic retention time used for water quality modelling (e.g. Plósz et al., 2013) to the very complicated CFD (Computational Fluid Dynamics) models used to model flow in specific structures in great detail (Fach et al., 2009; Isel et al., 2013). The model complexity of most operational models lay somewhere in between. The most used types of operational models are briefly described in the following.

2.4.1 Conceptual models

When very fast models are required, or when looking at a problem that is lumped by nature, such as total runoff from a catchment, conceptual models are often used. These are usually linear models whose parameters can be estimated efficiently from historical input-output comparisons. This means that historical time series of input (rain) and output (flow) must be available. The simplest of these models is the time-area model (Butler and Davies, 2004), which has a finite impulse response function. When only the time of concentration from a catchment is known and a finite response is expected, this model can be used. Another equally simple model is the linear reservoir model (Chow et al., 1988), which has an infinite impulse response that decreases exponentially towards zero. Cascades of linear reservoirs are often used to model the runoff from entire catchments (e.g. Breinholt, 2012; Thorndahl et al., 2013).

2.4.2 Stochastic grey box models

For real-time control purposes, the uncertainty of model estimates is just as important as the estimate itself. Therefore, the use of stochastic grey box models is emerging within urban hydrology. These models have a noise term incorporated in the model formulation itself, which means that the uncertainty of the model estimates is automatically included in the calculations. In contrast to classical black box models, grey box models can incorporate some physical parameters such as catchment area, concentration time and even basins and overflow structures. One drawback of these models is their dependency on historical data to calibrate both physical and noise parameters. For more detail see (Breinholt et al., 2011; Löwe et al., 2013a; Thordarson et al., 2012).

2.4.3 Distributed urban drainage models

Distributed physically-based urban drainage models (DUDMs), such as Mouse/Mike Urban, SWMM, InfoWorks etc. are actually a mixture of several model types. The various runoff generating processes from each sub-catchment are usually modelled with simple lumped models, while the routing of water in pipe systems is modelled by solving the full dynamic wave formulation of the one-dimensional Saint-Venant equations. **Figure 6** illustrates the main components of a typical DUDM.

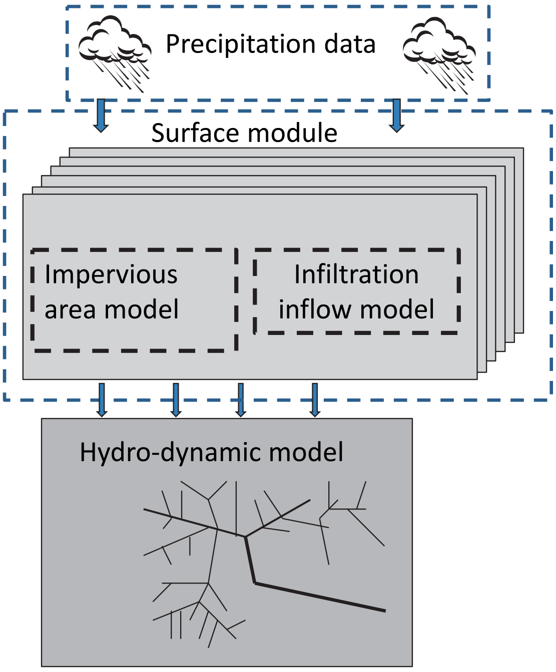

Figure 6: Schematic view of a Distributed Urban Drainage Model (DUDM).

DUDMs are divided into two main components: a surface module and a hydrodynamic model. The surface module converts precipitation data into inflow to the pipe system for each sub-catchment in the system, while the hydrodynamic model calculates the flow in the pipe system using the flow from the surface module as model forcing. The impervious area models are used to model the direct runoff (cf. 2.1), typically using the impervious area and the time of concentration of the sub-catchment as parameters. The impervious area can be determined with good precision from e.g. areal footage but the time of concentration is often just a qualified guess from the modeller. This does not have a big effect on the overall model results, however, since the time of concentration of the impervious surfaces usually is much smaller than the overall hydraulic response time of the drainage system. The models that govern the groundwater and direct infiltration are much more uncertain, since they depend upon complex processes in the soil matrix that cannot be observed directly and parameters that are hard to estimate. Since the timescale of the infiltration processes are comparable of size or bigger than the response time of the pipe system, the errors will not be evened out by the hydrodynamic model.

The hydrodynamic models rely heavily on physical data about the system, such as the diameter, roughness, slopes, and location of the pipes as well as descriptions of basins, weirs, pumping strategies, etc. This means that the models in principle are extremely over-parameterised, since they easily contain thousands of parameters, and therefore the individual parameters are impossible to calibrate. Fortunately most of the parameters can be extracted from databases of the physical system. The level and location of each pipe's start and end point are known exactly, and therefore the way the flow is routed through the system under normal circumstances is known by the model. The diameter and roughness of the pipes are often less well determined since sedimentation can change these as time goes by, which first of all affects the maximum capacity of the pipe. This means that the hydrodynamic model can be expected to be well behaved until the pipes are full – which typically will happen once every 1 to 2 years during heavy rain, since this is often used as a design criterion when dimensioning the pipes.

3. Data assimilation

3.1 State estimation

Data assimilation involves merging models with data, and in its broadest sense it can include state estimation as well as system and parameter identification (Liu and Gupta, 2007). In the current work, data assimilation is used exclusively in the sense of "state estimation" – adjusting the variables of a model using measured data to produce the most accurate estimate of the true state of the system. In this way the updated model state becomes a synthesis of the system knowledge present in the model and the information present in the observations up to the time of updating. The actual process of calculating the true state estimate is here called the *analysis* or *model update*, while propagation of the model forward in time until the next model update is called the *time update*.

Data assimilation methods can be divided into two main classes: sequential data assimilation, where only data available up to the time of analysis is considered, and retrospective assimilation (also called *smoothing*), where data that is newer than the analysis time are also included in the analysis. The focus in this work will solely be on sequential data assimilation, since this is the right choice for most online applications.

3.2 State-space models

For data assimilation, models are usually formulated in state-space. This implies that all the time dependent variables that are manipulated in the model are represented in the state vector $\boldsymbol{x}$. Each of the n individual variables in the state vector is called a "state variable". For simplicity, multiple state variables will be referred to as "states". The state vector is propagated forward in time from time t_k to t_{k+1} by model M:

$$\boldsymbol{x}_{k+1} = M(\boldsymbol{x}_k, \boldsymbol{\theta}, \boldsymbol{u}_{k+1}) + \boldsymbol{\eta}_{k+1} \tag{1}$$

where $\boldsymbol{\theta}$ represents the parameters of the model, $\boldsymbol{u}$ is model forcing and $\boldsymbol{\eta}$ is process noise (sometimes also called model noise).

Observations are related to the state vector through the observation equation:

$$\boldsymbol{d_k} = h(\boldsymbol{x}_k) + \boldsymbol{\varepsilon}_k \tag{2}$$

where $\boldsymbol{d}$ is a vector containing p observations, h is the observation function that maps the observations to the state-space, and $\boldsymbol{\varepsilon}$ is a vector representing the observation error. The observation operator can be complex in systems where the quantities observed do not correspond directly to state variables, but for the models used in this thesis the observed quantities correspond to specific state variables (local flows or water levels). In this case $h(\boldsymbol{x})$ equals $\boldsymbol{Hx}$, where $\boldsymbol{H}$ is a p-by-n matrix of zeroes and ones, with ones only for states where there is an equivalent observation.

In order to estimate the true state from equations (1) and (2), it is necessary to make some assumptions about the noise terms $\boldsymbol{\eta}$ and $\boldsymbol{\varepsilon}$. These noise terms can be very difficult to identify and quantify, and therefore – out of acknowledged ignorance and mathematical convenience – they are typically assumed to be zero mean, uncorrelated, Gaussian noise.

3.3 The Kalman Filter (KF)

If the process noise $\boldsymbol{\eta}$ and the observation noise $\boldsymbol{\varepsilon}$ are Gaussian and the model itself is linear, then the Kalman filter (KF) (Kalman, 1960) provides the optimal solution in terms of minimizing the mean squared error. The KF is basically a recursive application of Bayesian updating using the error covariance $\boldsymbol{P}$ that is estimated by the KF itself. $\boldsymbol{P}$ is derived by propagating the estimate of $\boldsymbol{P}$ from the previous analysis forward in time using the model operator and adding the process error covariance $\boldsymbol{Q}$:

$$\boldsymbol{P}_{k+1}^{b} = \boldsymbol{M}\boldsymbol{P}_{k}^{a}\boldsymbol{M} + \boldsymbol{Q}_{\boldsymbol{k}} \tag{3}$$

where $\boldsymbol{M}$ is the linear model operator and $\boldsymbol{Q}$ is an n-by-n matrix representing the process error covariance. The superscript "*a*" stands for "analysis" and is also referred to as an "update". Superscript "*b*" stands for "background" which is the values obtained by model propagation from the previous analysis step. If the model is not linear, a tangent linear model operator can be approximated from the actual model, in which case the filter is called the extended Kalman filter (EKF) (Evensen, 2009; Jazwinski, 1970).

Once $\boldsymbol{P}$ is known, the optimal correction (update/analysis) can be calculated as:

$$\boldsymbol{K}_{k} = \boldsymbol{P}_{k}^{b}\boldsymbol{H}^{T}(\boldsymbol{H}\boldsymbol{P}_{k}^{b}\boldsymbol{H}^{T} + \boldsymbol{R}_{k})^{-1} \tag{4}$$

$$\boldsymbol{x}_{k}^{a} = \boldsymbol{x}_{k}^{b} + \boldsymbol{K}_{k}(\boldsymbol{d}_{k} - \boldsymbol{H}\boldsymbol{x}_{k}^{b}) \tag{5}$$

$$\boldsymbol{P}_{k+1}^{a} = \boldsymbol{P}_{k+1}^{b} - \boldsymbol{K}_{k}\boldsymbol{H}\boldsymbol{P}_{k+1}^{b} \tag{6}$$

where $\boldsymbol{R}$ is a p-by-p matrix with the covariance of the observation noise, $\boldsymbol{x}^b$ is the background state, and $\boldsymbol{K}$ is the Kalman gain – a matrix which determines how much each state variable should be corrected as a result of deviations between the model and observations. The term $(\boldsymbol{d}_k - \boldsymbol{H}\boldsymbol{x}_k^b)$ is the difference between the observations and the background state in observation space, and is referred to as the model residual or the innovation. The combined effect of equations (4) and (5) is that the model is corrected from the innovation that is scale by the ratio between the model variance and the total variance of the model and observation in the measurement point. The corrections are distributed throughout the model according to the correlations in the model error between the individual state variables and the measurements. This implies that the corrections are larger the smaller the observation error is compared to the model error.

The propagation of $\boldsymbol{P}$ over time is the real key element in KF, but it is also the most costly operation because $\boldsymbol{P}$ has the dimensions n^2. In order to work around this issue, one can try to estimate a static $\boldsymbol{P}$ or $\boldsymbol{K}$, if the system dynamics are relatively constant. For many dynamic systems this is not a reasonable thing to assume, so the error covariance needs to be estimated sequentially in order to be able to use the KF analysis equation for updating.

3.4 The Ensemble Kalman Filter (EnKF)

In order to avoid problems associated with the linearization of non-linear models used in the EKF, Evensen (1994) introduced the ensemble Kalman filter (EnKF) – a Monte Carlo implementation of the Kalman filter in which all noise terms are included as random perturbations. The EnKF uses an ensemble of similar models that are propagated in parallel, albeit each with its own realisation of the stochastic noise terms, to estimate the error statistics required for Kalman filter analysis. In this way the model is used to propagate the error statistics, so there is no need to linearise the model, and at the same time the cost of handling the covariance is heavily reduced as long as the number of model states n are greater than the number of ensemble members m (also denoted as the size of the ensemble). **Figure 7** illustrates an EnKF setup with three ensemble members.

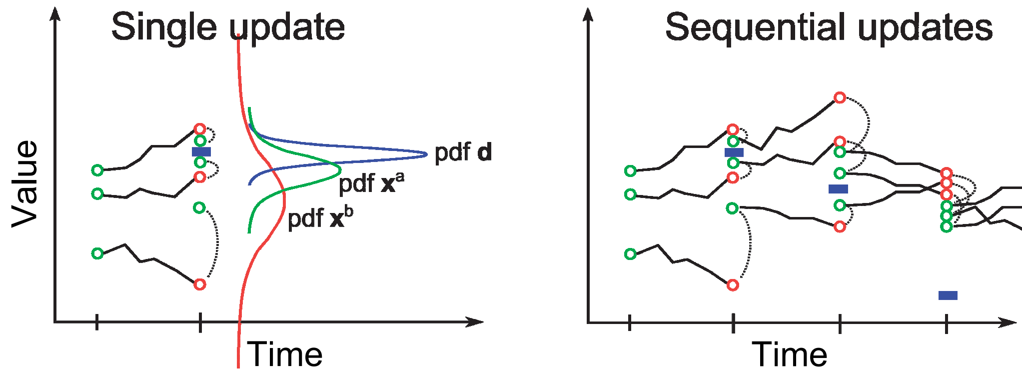

Figure 7: Single (left) and sequential (right) updates. The red dots are the background state values, while the green dots are the state values after the updates. The blue rectangles mark observations.

In the EnKF, the Kalman filter analysis (equation (5)) is applied individually to each member of the ensemble of background states. The Kalman gain calculation is based implicitly on equation (4), but the error covariance matrix is replaced with the ensemble covariance, which allows for the calculation of $\boldsymbol{K}$ without actually calculating $\boldsymbol{P}^b$. This is possible because the two main terms of equation (4), $\boldsymbol{P}^b\boldsymbol{H}^T$ and $\boldsymbol{H}\boldsymbol{P}^b\boldsymbol{H}^T$, can be calculated directly from the ensemble (Houtekamer and Mitchell, 2001).

The term $\boldsymbol{P}^b\boldsymbol{H}^T$ is an n-by-p matrix that represents the covariance between all individual states and the states observed in observation space:

$$\boldsymbol{P}^b\boldsymbol{H}^T = \frac{1}{m-1}\sum_{i=1}^{m}(\boldsymbol{X^b}_i - \overline{\boldsymbol{X^b}})(h[\boldsymbol{X^b}_i] - \overline{h[\boldsymbol{X^b}]})^T \tag{7}$$

where $\overline{\boldsymbol{X^b}}$ is the background ensemble mean, calculated as:

$$\overline{\boldsymbol{X^b}} = \frac{1}{m}\sum_{i=1}^{m}\boldsymbol{X^b}_i \tag{8}$$

and h is a measurement operator that does not need to be linear, since it can be applied individually to each ensemble member when calculating $\overline{h[\boldsymbol{X^b}]}$:

$$\overline{h[\boldsymbol{X^b}]} = \frac{1}{m}\sum_{i=1}^{m}h[\boldsymbol{X^b}_i] \tag{9}$$

The p-by-p matrix $\boldsymbol{HP}^b\boldsymbol{H}^T$ is the covariance between the observed states in observation space:

$$\boldsymbol{HP}^b\boldsymbol{H}^T = \frac{1}{m-1}\sum_{i=1}^{m}(h[\boldsymbol{X^b}_i] - \overline{h[\boldsymbol{X^b}]})(h[\boldsymbol{X^b}_i] - \overline{h[\boldsymbol{X^b}]})^T \tag{10}$$

The standard EnKF implementation implies the use of perturbed observations, whereby realisations of (preferably Gaussian) noise are created from the observation uncertainty description and applied to the observations before using the analysis equation, which means that each individual ensemble member is updated using a different value for the same observation. Without the use of perturbed observations, the EnKF will reduce the ensemble variance too much (Burgers et al., 1998).

In contrast to the standard KF, where only additive process noise can be used, there are no restrictions in the formulation of the process noise when using EnKF. This means that the process noise can be specified based on physical considerations about the noise, which is a desired property when using physically based models like DUDMs, and can be chosen to be e.g. state proportional.

3.5 The Deterministic EnKF (DEnKF)

An inherent problem in any ensemble representation is that of sampling errors. When using small ensembles this problem is being enlarged by using perturbed observations as in the standard formulation of the EnKF. To overcome this problem Sakov and Oke (2008) proposed the Deterministic Ensemble Kalman filter (DEnKF), in which observations are not treated as random variables (thus the name "deterministic"). Despite the name the method is still a statistical DA method that seeks to reduce the uncertainty in the model estimates in a probabilistic setting. Therefore the DEnKF will only be referenced by its abbreviation in the rest of this thesis to avoid unnecessary confusion in regards to the purely deterministic DA methods described in section 0. In order to avoid excessive reduction in ensemble spread as a consequence of omitting the perturbation of the observations, the DEnKF analysis is split into two steps: first the ensemble background mean $\overline{\boldsymbol{X^b}}$ is updated using the standard analysis equation (5), following which the anomalies for the ensemble are updated using only half the Kalman gain. The factor of one half was derived from the fact that the EnKF without the use of perturbed observations in the linear case reduces the error covariance too much by a factor up to two, compared to the standard Kalman filter.

Anomalies $\boldsymbol{A}$ are calculated as deviations from the background mean:

$$\boldsymbol{A}^b = \boldsymbol{X}^b - \overline{\boldsymbol{X}^b} \tag{11}$$

after which the background anomalies are updated:

$$\boldsymbol{A}^a = \boldsymbol{A}^b - \frac{1}{2}\boldsymbol{KHA}^b \tag{12}$$

The updated ensemble is now constructed by adding the updated ensemble mean to the updated anomalies:

$$\boldsymbol{X}^a = \boldsymbol{A}^a + [\overline{\boldsymbol{X}^a}, \dots, \overline{\boldsymbol{X}^a}]) \tag{13}$$

Due to the different mean and anomaly updates, the method is limited to linear measurement operators. Other ensemble-based data assimilation methods exist that does not rely on perturbed observations, but Sun et al. (2009) indicate that the DEnKF is the more robust choice and the method that performs the best for small ensemble sizes; therefore, the other methods will not be considered in this thesis. Furthermore, DEnKF allows for standard Schuur-product-based localisation, which is described in section 3.7.1.

3.6 Partial Ensemble Kalman Filtering (PEnKF)

Partial Ensemble Kalman Filtering is developed during this thesis to enable the EnKF to use range limited observations, such as the water level measurement shown in **Figure 4**. The key element in the method is that if observations indicate that an observed quantity is outside the observable range of a gauge, the members of the ensemble that are within the observed range are adjusted towards the edge of the observable range using an imaginary observation at the edge, as illustrated in **Figure 8**. Meanwhile, ensemble members that are in fact outside the observable range are not updated. Since only a part of the ensemble is updated, the method is referred to as “partial updating”. The theoretical justification for the method can be seen in **Paper VI**.

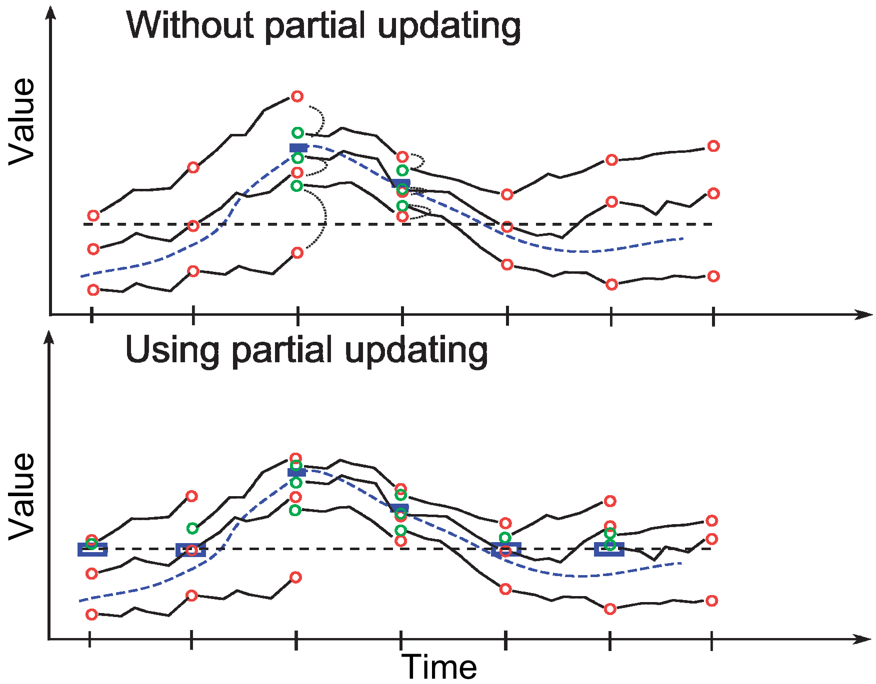

Figure 8: Sequential ensemble updating, with and without the use of partial updating when a gauge has a lower observation limit (dashed black line). The red dots are the background state values while the green dots are the state values after the updates. Solid blue rectangles are actual measurements, while empty blue rectangles indicate the virtual measurements used for the partial updating when no actual measurements are available (**Paper VI**).

The method was evaluated using perfect model experiment forecast testing on both linear and non-linear reservoir cascade models (**Paper VI**). The results show that partial updating significantly improves forecast quality in cases where the observable state often falls outside the interval observable by the gauge. Besides enabling the use of range limited observations, the method can ease the process of including irregular observations in an EnKF setup. Any signal that can be interpreted as a water level being higher or lower than a certain value can be utilised with partial updating. Examples of such signals are the status of bendable weirs or the power consumption of pumps. Furthermore, the method can be used to partially disable updating when an observed value enters a part of the state-space where the model is not expected to behave like the physical system.

3.7 EnKF tuning

Due to the assumptions and simplifications in the model, the filter and the forcing data, it is often necessary to perform a significant amount of heuristic tuning of the EnKF setups. This can be a very time-consuming process and is furthermore a mathematically unappealing, but often necessary, feature of ensemble filters.

3.7.1 Localisation

A limited ensemble size leads to spurious correlations in the ensemble between state variables that are far apart, and the smaller the ensemble size the bigger the problem will be (Houtekamer and Mitchell, 1998). Furthermore, erroneous correlations can arise due to wrong assumptions and misspecifications concerning the structure of the filter noise on forcing, states, parameters, etc. If erroneous long-range correlations are not dealt with, they will lead to unjustified long-range corrections to the model. In order to avoid this problem, it may be necessary to use one of the various localisation schemes that ensure that model adjustment decreases with the distance to the observation (Hamill et al., 2001; Houtekamer and Mitchell, 2001; Kepert, 2009; Oke et al., 2007). It is, however, not easy to determine what would be a reasonable measure of distance for a localisation scheme for an urban drainage model. Correlations in rainfall rely on actual distance, but in terms of hydraulics the distance should be measured along the pipes; however, as soon as there are backwater effects, the distance should rather be measured in the vertical direction. Furthermore, RTC and pressurised pipes complicate the matter; for instance, what is the correct measure of distance when water is pumped from one end of a catchment to another, thus creating some very real correlations between two remote parts of the model, or when the level in one basin controls flow at the opposite end of the catchment?

In the absence of a reasonable measure of distance for a localisation scheme to depend on it could be tempting to use a precautious localisation scheme with a very short localisation radius measured in geographical distance. In this way the impact of the updating is confined to a limited area and it seems reasonable to assume that this will limit the potential harm done by erroneous corrections. This is, however, not necessarily the case. Consider a case where downstream flow observations are used to update a model with a lot if slowly changing infiltrating inflow and where a very short-ranged localisation scheme is used, which implies that only the close-by catchment are corrected. Since the filter works recursively, it will keep on trying to make the model compensate for the erroneous flow, and therefore the close-by catchments will end up being attributed the entire correction for the error caused by infiltration from all over the system. This illustrates that when modifying the gain from computed gain, the update balance is changed, which can have the consequence that what should be a precautionary measure ends up creating substantial erroneous corrections.

3.7.2 Inflation

Bayesian-based ensemble updating, such as EnKF, continuously reduces the ensemble variance (since the product of two Gaussians has a smaller variance than any of the originals). This, and the fact that most errors related to ensemble-based filters tend to lead to underestimating error covariance (Furrer and Bengtsson, 2007), can lead to ensemble collapse. This occurs when the variance of the ensemble becomes much smaller than the variance of the observations, which means that the observations are ignored by the filter, and the model is therefore free to diverge towards any value far from the observations. This can be counteracted by using inflation; a heuristic method that seeks to increase the ensemble spread by multiplying ensemble anomalies by a certain factor during each update cycle. Inflation strategies can be based on constant as well as dynamically estimated inflation (Anderson and Anderson, 1999; Anderson, 2007; Li et al., 2009; Mitchell and Houtekamer, 2009; Ott et al., 2004).

3.7.3 Dampening

The simplest form of tuning is damning. This implies multiplying the corrections with a dampening factor between zero and one, which thereby “dampens” the response of the filter (makes it react slower). The main motivation for this method is to avoid ensemble collapse as it is done in (Hendricks Franssen and Kinzelbach, 2008) or to obtain a more stable update without sudden large corrections as it is done in (Erdal et al., 2014). If the purpose of dampening is to obtain stable updates this can implicitly be achieved by overestimating the observation uncertainty, since this result in corresponding smaller corrections.

3.8 Other ensemble based DA methods

Besides the standard EnKF and the DEnKF mentioned above, a number of other variations of the EnKF exists, of which the most prominent is the group of Ensemble Square Root Filters (EnSRF). A review of four of these methods can be found in Tippett et al., (2003). These methods, like the DEnKF, uses a separate Kalman gain for the update of the ensemble anomalies in order to produce an error covariance that matches that of the Kalman filter without the use of perturbed observations. Where the DEnKF only approaches the desired error covariance by multiplying the Kalman gain with ½, the EnSRF calculates the modified gain in order to match the error covariance exactly in the linear case. The main drawback of this method is that calculation of the modified gain makes it difficult to use covariance localisation, which is assumed to be needed at some point for updating DUDMs.

Another important group of ensemble based data assimilation methods are the Particle Filters (Gordon et al., 1993; Arulampalam et al., 2002). These differ from the Kalman filters by not actually updating the states of the models. Instead each model is assigned a probability that is computed based on comparisons with observations, and this probability is then used as a weight for calculating the probability distribution of the model estimates. The advantage of this method is that it requires no or very few assumptions about the distribution of the errors, and it is furthermore not necessary to be able to alter the state variables of the models. The main drawback is that the method requires many more ensemble members (particles) than Kalman filter based methods, and therefore the Particle Filters are not relevant for high-dimensional systems like DUDMs. Experiments with hybrids between particle filters and Kalman filters, such as (Delft et al., 2009), have shown promising results in synthetic experiments using a simple conceptual, close to linear, rural rainfall runoff model but it is not clear if these results will hold in the real world.

3.9 Testing DA methods

When quantifying the performance of a simulation model, it is normal to compare the simulation result with an equivalent independent observation time series. When a model is included in a DA setup, however, it is natural to use all available observations for the updating, which means that there are little observations left for validating the effectiveness of the DA scheme. The models in the focus of this thesis are multi-purpose distributed models for which both the current state of the system as well as model forecasts might be of interest. In order to test the effectiveness of a DA scheme it is necessary to test whether state estimates other than the observed states included in the DA do actually improve. The options for carrying out this task are described in the following.

3.9.1 Real data vs. perfect model experiments

A method often used for validating DA schemes is "perfect model experiments" (sometimes also referred to as "twin tests" in literature), in which the model itself is used to create an artificial truth by using perturbed model forcing, parameters and process noise with known statistics. The benefits of this method are that the true-state vector is known and that there are no limitations to the length of the observation time series. Furthermore, the fact that the model behaves perfectly and error statistics are known makes it is possible to conclude on the isolated, best-case effect of the DA scheme on the specific setup. Therefore, perfect model experiments is a natural choice for testing new DA methods or for testing proof of concept for specific model types.

By assuming a perfect model and known error statistics, the DA setup will, however, perform better than realistically achievable in real-life applications where none of these assumptions will hold. The effect of even small model imperfections can systematically degrade state estimation (Judd and Smith, 2004), so any DA setup to be used in real-life applications, if possible, should be tested using real observations.

3.9.2 Forecast error testing

The point value of a forecast with a hydrological model is dependent on the previous values of upstream states. If the forecast horizon is very short, the previous value of the states close to the validation point will determine the value of the forecast, while a long-range forecast will be dependent upon the history of the states far upstream. This means that if only downstream observations are available, then the global effect of a DA scheme can still be assessed by assessing the quality of forecasts based on the updated model for all relevant forecast horizons. The danger of using this kind of lumped validation for a distributed model is that excessively high values in one part of the model can be compensated for by overly low values in another part of the model – an issue which is not visible in the forecast. Therefore, this kind of test is most suitable for conceptual models in which the level of detail corresponds better with the number of observations available, although it can be used for distributed models as long as the limitations in the method are acknowledged.

The workflow in this kind of testing involves initiating forecasts from the analysed state every *dT* minutes, running the forecasts for the desired forecast horizon $T_{forecast}$ and adding the forecasted results to the produced forecast timeseries. The total simulation cost for this kind of validation is $T_{forecast}/dT$ times the cost of a single deterministic simulation of the validation period. This means that the cost of assessing DA performance by using a 10 hour forecast time series with a discretisation of 30 minutes is 20 times that of a normal simulation of the validation period. Hence, it can be rather costly to use this validation method on very large models.

An important issue when validating through forecasts is choosing what model forcing is used when producing the model forecasts. If forecasted forcing is used, the forecast system is tested as a whole, and this is therefore a natural thing to do before an online model is taken into use for decision making. If the purpose of the test is only to assess how good a DA scheme is at estimating the true state of the system, then *perfect forecasts*, which are the observed model forcing from the relevant time steps ahead, should be used. This is possible since testing is usually done on historical data.

3.9.3 Cross validation

Instead of testing the quality of updates on upstream states indirectly by looking at forecasts of various lengths, it is much more computationally efficient to look directly at the relevant states, since this does not require producing multiple long forecasts. This is, however, only possible for observed states, which means that this is seldom an option for conceptual models where individual state variables seldom represent a physical value that can be measured. This is possible for distributed models, but for operational models the high system dimensions will usually make it desirable to use all the observations available for the updating. Therefore cross validation for DA on DUDMs is foremost relevant if observations are available that for some reason cannot be utilised by the DA scheme or in connection with perfect model experiments, in which case it is possible to produce all the observations desired.

3.9.4 When to use which method

When a specific real-life model is going to be used in a DA setup, it would be best to test the updated model with measured data, in order to test the DA system in the setting in which it is to be used. For a general purpose distributed model this will require lots of observations distributed all over the system, which are not used for updating. This kind of data abundance is very rare, which means that this type of testing is often not an option for distributed models. Therefore, the most realistic option for testing DA for DUDMs is to perform thorough perfect model experiments, to see if the DA setup works under idealised conditions, followed by real data forecast error test with the datasets available. When using small conceptual forecasts models tailored specifically for producing forecasts for model predictive control, the appropriate choice of validation is forecasts error testing using historical data.

Table 1 shows the author's opinion about when to use which validation method and in which of the articles included in this thesis the methods have been used.

Table 1: When to use which validation procedure and in which of the included articles the procedures have been used.

Method: / Data:	Cross validation	Forecast error testing	**Useful for:**
Actual data	**Paper II** **Paper IV**	**Paper III** **Paper IV** **Paper V**	Final test of DA applications
Synthetic data (Perfect model experiments)	**Paper V**	**Paper I** **Paper VI**	DA principles Proof of concept
Useful for:	Distributed models	Conceptual models Distributed models when data is sparse	

4. Model forcing for updated models

Rainfall data used as forcing for runoff models has a significant influence on model estimates as well as the magnitude and structure of model uncertainty. Since most urban runoff processes are relatively fast compared to rural hydrology, any short-term uncertainty in rainfall data has a more significant impact on the model within urban hydrology. Snapshots are always more uncertain than values accumulated over time, but just as important is the fact that the spatial variability of rain is much greater at shorter than longer timescales. For example, a raingauge placed 10 km away says very little about the current rain intensity, but it can be used pretty accurately to estimate the total yearly rainfall. Therefore the question regarding measuring the rain is not only a matter of using the technique with the lowest instrumental uncertainty when assessing local rain intensity, but also a matter of being able to estimate the spatial distribution of the rainfall. For this reason weather radars are becoming more popular as providers of rainfall estimates for urban runoff modelling, although raingauges are still the far most common choice. In the following section, the properties of these two rain estimation methods are compared along with the effect they have on model updating.

A runoff model accumulates rainfall estimation errors, which can then be compensated for using data assimilation. Due to the important role of rainfall estimates on model states, these will to a great extent determine the error structure within the model. When the error structure is known, it is possible for a DA scheme to correct for the errors based on relatively few observations from the system. This makes it less essential that rain estimates are at the correct level when a model is updated efficiently, as long as the relative distribution of the rain in space and time is correct.

4.1 Raingauges

Most raingauges work by collecting the rain water that passes through an opening in the gauge with an area of a few hundred square centimetres. The rain intensity is then calculated by measuring the collected volume of water within a given time interval, which can be done in many different ways. Raingauges can be very accurate within close distance to the gauge, and their instrumental observation uncertainty is usually very low. A laboratory study of existing commonly used raingauges has shown that these easily comply with a 5% accuracy limit for 1 minute data for all relevant intensities (Lanza and Stagi, 2009). On top this we need to consider the effect of wind on the gauges, which typically can make them underestimate the rainfall with up to 15% (Neff, 1977; Sevruk, 1996). The main errors found in runoff models when using gauges as input are however not from instrumental or catching errors but rather from sampling errors due to a limited number of gauges. The required density of raingauges, in order to sample the spatial variability of rain properly for modelling the runoff from a 51 ha urban catchment was found to be as high as 3 gauges per km^2 by Cooper and Fernando (2009) while (Berne et al., 2004) found that a temporal-spatial rainfall data resolution of 3 minutes and 2 km, respectively, is required in order to model the runoff from urban catchments of a size of 100 ha to a satisfactory level. Spatial variability, however, differs immensely depending on the type of rain event. For frontal-type rains, variability is low and a few gauges would be able to sample this rainfall for an entire urban area, while convective showers are much more local and a much larger density of gauges is needed.

In order to apply the point data from a raingauge to a distributed model, some sort of interpolation is necessary. Without considering the movement of the rain (which is hard to estimate from raingauge data), the data will be applied instantaneously to the whole area. This means that the use of raingauge data will often result in time-displaced runoff hydrographs, as illustrated in **Figure 9**. Another typical feature of modelled hydrographs based on raingauge data is exaggerated peaks. This is due to the fact that the point variability of the rain is greater than the areal variability.

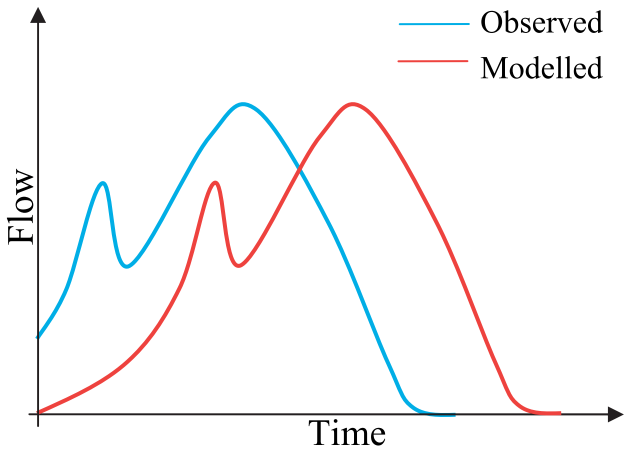

Figure 9: Ideal model hydrograph when the only error is due to the location of the raingauge outside the centre of the catchment.

Without information about the spatial variability of rain it is very difficult for a DA scheme to include this aspect. When using an ensemble-based DA scheme it is preferable to be able to create perturbed model forcing with the right spatial and temporal statistical properties. Without any information about the spatial variability of the rainfall, this is not a feasible task.

4.2 Radar rain estimates

Rain-detecting radars measure the energy reflected by raindrops from an electromagnetic pulse emitted by the radar itself. The distance to the rain is then calculated by measuring the time it takes for the signal to return to the radar. The amount of energy reflected from a rain-filled atmosphere is related to the reflectivity Z, which is given by (Rinehart, 2010):

$$Z = \sum_{vol} D_i^6$$

where D_i is the diameter of a rain drop. Based on this, and on an assumption about the Drop Size Distribution (DSD) of the rain drops, it is possible to estimate the volume of water in the air and the rain rate. Numerous types of radars exist, each with different ways of relating reflectivity to rain rate, but they are all sensitive to the DSD, which is not directly observable. Perhaps for this reason radar rain estimates are generally associated with substantial amounts of uncertainty. A meta study by McMillan et al. (2012) shows that the typical standard deviation of the error of radar rain estimates as a proportion of the rain rate lies in the range 0.3 to 0.5 for hourly data.

The distributed nature of radar data fits unquestionable better to the distributed nature of DUDMs than the point measurements from raingauges. This is, however, not enough to compensate for the errors in the radar rain estimates. An interesting difference between radar and raingauge estimates is that while the areal rainfall intensity estimated by raingauge becomes increasingly more uncertain in line with increasing area, radar estimates become less uncertain. This phenomenon is shown in **Figure 10**, which displays results from a study including data from both a modern weather radar, with polar pixel sizes no larger than 600 m times 250 m, and a dense network of raingauges (Seo and Krajewski, 2010). It is quite clear that the raingauge data is much more accurate than the radar data on most scales in space and time relevant to urban runoff modelling. For 15 minute averages the raingauges perform the best up to approx. 5.5 km grid size while the corresponding grid size is more than 7 km for hourly data.

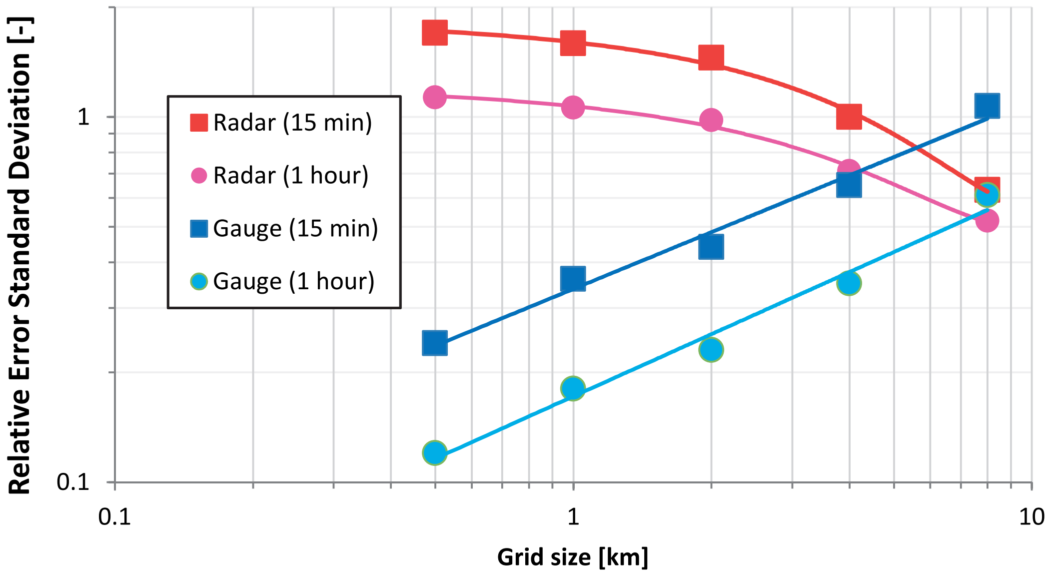

Figure 10: Relative error standard deviation of raingauge and radar rainfall estimates as a function of spatial scale. Data from Seo and Krajewski (2010).

4.3 Merged radar-raingauge estimates

Since radar data and raingauge data to some extent have opposing properties, they complement each other quite well in the sense that raingauges are good at estimating local intensities, while radars are good at estimating the spatial distribution of rain.

It is quite obvious that a combination of these data can be beneficial, and this is indeed undertaken in a number of operational systems (e.g. Rasmussen et al., 2008; Thorndahl et al., 2013) as well as in numerous research studies (Borup et al., 2009; Gerstner and Heinemann, 2008; Goudenhoofdt and Delobbe, 2009; Löwe et al., n.d.; Thorndahl et al., 2014). The merging of radar and raingauge data can be done in many ways. In (Thorndahl et al., 2014) comparisons with raingauge data are used to bias correct and scale the radar data, while (Löwe et al., 2013b) uses Kalman filtering for the job. In **Paper II** the radar rainfall estimates are dynamically adjusted by continuously multiplying radar data with a factor calculated between radar data and raingauge data from the recent past (10-25 minutes). The quality of the rainfall estimates is assessed by comparing measured and modelled water levels at an overflow structure, where the model is a DUDM that is forced with the various rainfall estimates. The results show that the dynamically adjusted radar data perform similarly to a raingauge situated in the middle of a small 64 hectare urban catchment and much better than the gauges situated 2-4 km from the catchment that is used for adjusting the radar data. This procedure is suitable for improving the rainfall estimates in an area where there is already decent raingauge coverage. Nielsen et al.(2014) later confirmed that dynamic adjustment to raingauges is required for the type of radar used in **Paper II** if this is to be used to represent the short term variability of the rainfall.

The merged rain products might be of a higher quality in terms of deviations from the actual rain rate, and they are likely to be the better choice in most simulation studies. For updated models the situation is complicated by the fact that an updated model foremost needs the correct description of the temporal and spatial error structure of the rain rather than the absolute level of the rain, and this might very well be obscured in the merging process.

4.4 Time-displaced model forcing

The mean rain cell velocity in Northern Europe is approximately 10 m/s (Marshall, 1980; Niemczynowicz, 1987), which means that a typical rain cell can cross a 6 km-wide urban area in 10 minutes. This might seem as an insignificant amount of time in the light that such a catchment can have a concentration time of an hour or more, and for offline simulations the resulting 10 minute displacement in the modelled hydrograph does little harm. When the model is being updated from system observations, however, there will be a lack of synchronisation between model forcing and the observations. This means that the impact of a rain cell can be included twice: first due to delayed model forcing and second due to an update that corrects the model to adjust for the delayed model response following delayed forcing. This is illustrated in **Figure 11** for a case where the model is updated to reassemble observations 100%.

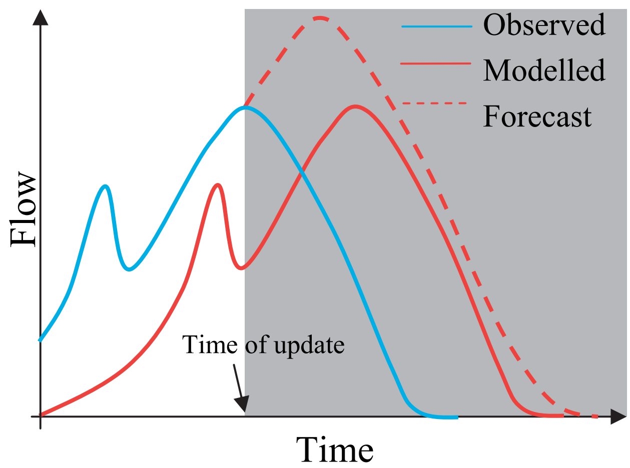

Figure 11: The dashed line shows a single model forecast made from the time of update using a model that has been updated to match reality but using (time displaced) raingauge data as model forcing.

Since radars measure the rain almost at the right place at the right time, time-displaced forcing is an issue related foremost to the use of raingauge data. This means that by looking isolated at the impact of using time-displaced model forcing on an updated model and comparing this to using model forcing with some other well-understood error statistics that can be attributed to the use of radar data, it is possible to compare the suitability of raingauge and radar data for updated models. This is done in **Paper I**, where the impact of using time-displaced model forcing for a simple conceptual updated model is compared with biased model forcing in a perfect model experiment. By using a simple linear time area model, and benchmarking forecast performance using a function of the squared errors of the outflow from the model, the study's conclusions surprisingly become independent of the catchment time of concentration as well as the direction of the time displacement. A result from the study can be seen in **Figure 12**, which shows that, for example, a 10-minute time displacement of model forcing compares to 100% biased model forcing when looking at the 10-minute forecast. Note that 100% biased model forcing corresponds to using no model forcing at all or to doubling the model forcing, while bias above 100% only makes sense for positive errors. The pattern from the 10-minute displacement is also seen for the 5- and 20-minute time displacements, which means that if the purpose of the model is to make forecasts that are shorter than the expected time displacements, it is thereby better not to use raingauge data at all.

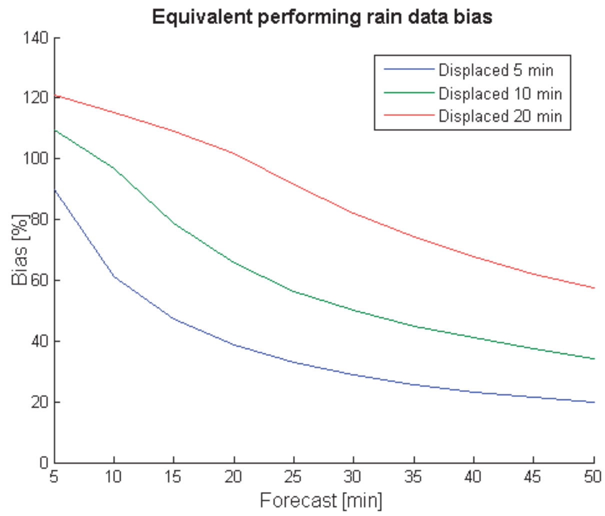

Figure 12: Impact of time displacement on updated model forecast quality measured in equivalently performing biased rain data (**Paper I**).

The study also shows that the relative negative impact of time displacement decreases with the forecast horizon. This means that if the model is used for long forecasts, or if it is updated very infrequently, the quantitative accuracy of the rain data is more important than the temporal displacement.

The study assumes that the raingauge measures rainfall displaced in time, but otherwise perfectly. This means that the raingauge performance can be seen as an idealised best case performance. Hence, the study justifies that radar data can be of significantly worse quantitative quality than raingauge data and yet still be the better choice for updated models.

5. Deterministic updating of distributed urban drainage models

In many cases it is impossible or undesirable to use an advanced statistical DA method to update a DUDM. One reason could be that the model is simply so computationally demanding that it would be too costly to run a sufficiently large ensemble to allow for ensemble-based methods. Another reason could be that not all model states in a commercial model can be controlled, as was the case for the DUDM used in **Paper III**. Finally, there might not be much to gain by choosing a sophisticated complex DA scheme if the data available does not support it.

In the following, a number of options for assimilating observations into a DUDM, without propagating ensembles or covariance matrixes forward in time, are discussed. Common to these methods is that they update model states to a single deterministic value without producing uncertainty estimate of the states, so these methods are herein referred to as “deterministic updating methods”.

5.1 Point-wise updating

The only recognised commercially available DA method for DUDMs is the MIKE UPDATE method by DHI, which works by updating water levels point-wise at the observed states to the observed value (**Paper IV**). This is done by inserting a correction flow that corrects for the difference between the model and the observation. It is possible to dampen the correction by applying a user-defined factor. This kind of updating is extremely simple but, as shown in **Paper IV**, it can improve the forecast skill of a model considerably when a major part of the water is routed through basins with a water level gauge. The method does however have some severe shortcomings. Since model uncertainty is not estimated dynamically, the only way to weigh the observation uncertainty against model uncertainty in the updating is through the user defined dampening factor. This means that there is a conflict between having efficient updating and wanting to avoid transferring observation errors directly to the model. Only places in the system where the relationship between water level and flow is very well known is suitable for this kind of updating, which foremost limits the use of this method to basins. A 5 cm water level difference in a 5 metre-deep basin means very little to the outflow, while a similar difference in a pipe with some gradient can have a huge impact on the flow. If the method is used in basins that usually fill up and empty rather slowly, time displacement issues as described in section 4.4 are likely to be of only minor importance. The method can be regarded as a borderline case of an extremely localised Kalman filter with constant gain in which the Kalman gain in equation (5) is a matrix of zeros except for the index corresponding to the observed state, for which the gain is equivalent to the dampening factor. This means that the Kalman gain in case of a single observation would look like:

$$\boldsymbol{K} = [0,0,0 \ldots . f \ldots . ,0,0]^{\mathrm{T}} \quad (14)$$

where f is the dampening factor of the point-wise updating.

5.2 Constant gain updating

A pragmatic way to use a Kalman filter-like method is to overcome the propagation of the covariance matrix forward in time by using a time-constant gain. This can then either be a user-defined gain, as suggested by Madsen and Skotner (2005) for river flow forecasting, or a constant gain that can been estimated by offline ensemble simulations. This kind of updating has been used with some success within e.g. oceanography (El Serafy and Mynett, 2008; Heemink and Kloosterhuis, 1990), river flow forecasting (Madsen and Skotner, 2005) and surface-water hydrology (Brocca et al., 2010) and due to its computational efficiency it would be a natural method to use in urban hydrology. The prerequisite for constant gain updating to function properly is, however, that the optimal gain does not vary too much, which means that the dynamics of the system should not vary too much in time. This is often not the case in DUDMs, as illustrated in **Paper V** where the gain a few kilometres from a level gauge is found to vary easily with a factor of 10. The consequence of using a gain that is too high is that the DA scheme will start to overcompensate for previously made erroneous corrections, in which case the model will become unstable. This means that it is not an option to use a time averaged gain. To avoid this situation the minimum offline detected gains could be used, but this would severely reduce the effectiveness of the DA scheme. Despite the above consideration, the feasibility of using a constant gain was tested and the results were very much as expected: in order to achieve a stable system the gain had to be very small or the updating very localised – and thus the update was not very effective. Using the constant gain method with a user defined gain, as in (Madsen and Skotner, 2005), the Kalman gain using a single observation could look like:

$$\boldsymbol{K} = [0, . . ,0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.3, 0.1, 0, . . ,0]^{\mathrm{T}} \quad (15)$$

where the non-zero values are for the states that are to be affected by the updating and the highest value is at the observation point. Note that if the method is localised to only the observation point the method corresponds to the point-wise updating in section 5.1.

5.3 Slow-changing inflow correction

Updating hydrodynamic states in a DUDM can be problematic from a stability point of view, and furthermore it might not be possible to control the hydrodynamic state variables with many commercially available DUDMs. It is, however, not always necessary to update hydrodynamic states directly in order to achieve a substantial reduction in the model errors. In many systems a substantial part of the inflow is related to infiltration processes, as described in section 2.1, which follow timescales much higher than the hydraulic response time of the pipe system. Infiltration processes are usually modelled with simple linear models that can be updated more easily. This was done in **Paper III**, where the hydrological states of the Rainfall Dependent Infiltration and Inflow module (RDII) (DHI, 2009) of a Mike Urban model were manipulated to compensate for downstream model errors. In short, the method estimated the part of the model error that can be attributed to slow-changing processes and adjusted upstream RDII states to correct for this part of the error. In order to maintain a stable system the responses were dampened using a linearised version of the model response to changes in RDII states. This enables much faster corrections than just using a dampening factor and it still ensures stability. The method does not, however, translate nicely to a form that resembles the classical Kalman filter update equations of section 3.3.

A case study using measured flow data to update and validate a Mike Urban model for the Danish catchment of Ballerup (**Figure 13**) was conducted.

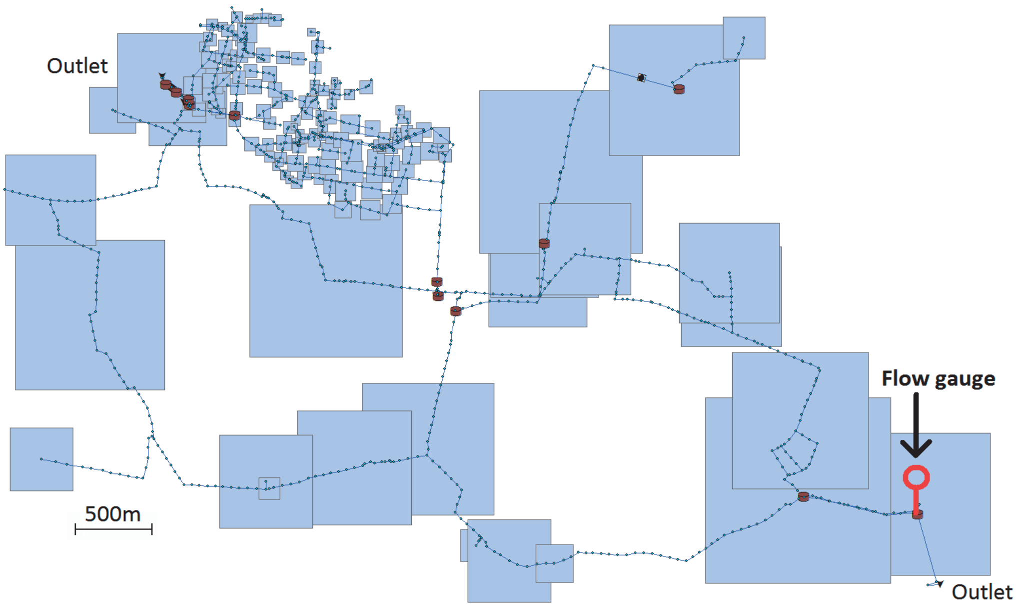

Figure 13: View of the distributed Mike Urban model of the Ballerup catchment. The sub-catchments of the surface module are shown as square boxes that have the same centre and areal size as the area they are representing.

The results showed that the method significantly improves flow forecasting at least 10 hours ahead (see **Figure 14**). Note that R^2 does not start close to 1 for the 0 hour forecasts, as would be the case for a filtering update of the entire model with good quality observations, because only the most upstream states of the model are updated. Therefore, the improvement in the 0 hour forecast can be seen as an indication of globally more accurate model estimates.

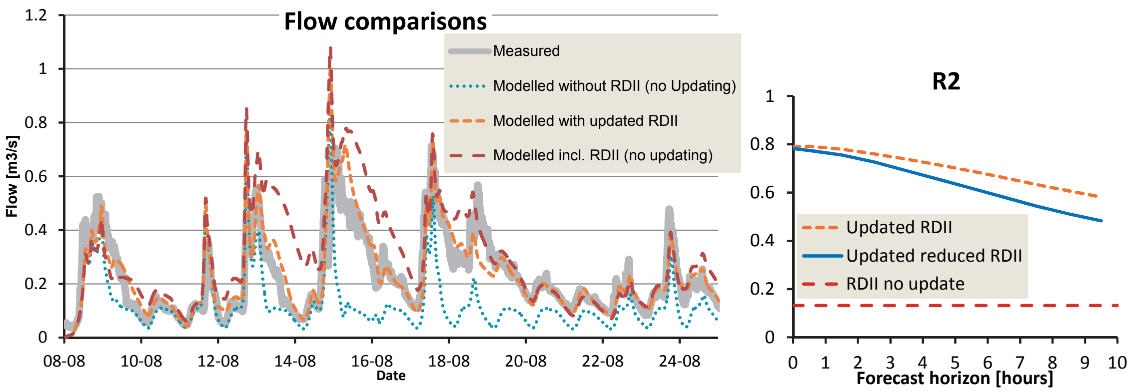

Figure 14: (Left) Measured and modelled runoff when using the model with and without the RDII module and when updating RDII module states. (Right) Nash-Sutcliff R^2 for up to 10-hour forecasts. The solid line occurs when the RDII module has been reduced to only groundwater storage and the two *Immediate Response* reservoirs (**Paper II**).

It might not be possible in the given example to obtain a much better result by using a more advanced scheme. Since the rain data comes from a single raingauge it does not indicate very much about the spatial distribution of the rain, while flow observations do not contain any information about the origin of the water, so Bayesian updating (like the KF) – based on rainfall-induced model error covariance – will end up distributing the correction close to uniformly over the catchment. Furthermore, an attempt to update fast dynamics will be counteracted by temporal errors caused by sparse rain input.

5.4 Discussion

The deterministic DA methods can take a model a long way towards being a useful online model. A combination of the point-wise updating of basins and the slow-changing inflow correction presented in section 5.3 may be sufficient to keep a model in touch with reality most of the time, even in areas with limited rain data coverage, and thereby ensure good initial conditions before the start of the next rain event. If a probabilistic dimension is required for model forecasting in combination with deterministic updating, this can only be achieved for the observed states by using error modelling.

The main limitations of the deterministic methods are related to the lack of updated model uncertainty estimates, without which it is impossible to determine how much the observation should be trusted compared to the model. Furthermore, none of the methods are suitable for global updating of hydrodynamic states.

6. Using EnKF to update distributed urban drainage models

Even though statistical DA methods like the EnKF are much more computationally expensive than the deterministic methods described in the previous chapter, there are good reasons for aiming for these for updating DUDMs. The uncertainty of model estimates from a DUDM will change over time as a result of changing uncertainty of rainfall estimates, changing hydraulic and hydrological conditions and previous data assimilated into the model, etc. A frequently occurring example of changing model uncertainty for a DUDM is the modelled outflow from a catchment that is very uncertain during a rain event due to the uncertainty of the rainfall estimates, while it is better determined by the model after the event when the flow is dominated by the outflow from basins in the system. Therefore, the optimal DA method should concurrently estimate the model error in order to estimate how much weight should be given to the observation in the analysis. This is done by the EnKF while also estimating the optimal spatial distribution of the corrections throughout the model. Since the EnKF uses the model itself to propagate the error statistics forward in time, all the aspects of the physical behaviour of the system that has been included in the model description, are also included in the evolution of the model error. This is a powerful feature when used on DUDMs since these incorporate all the most important physical properties of the system.

In order to determine the suitability of the EnKF for DUDMs it is important to know if the filter can function with an ensemble of feasible size and if the filter can work under the rapidly changing hydraulic conditions often present in the drainage system. This is investigated in the current chapter (based on **Article V**) along with the potential for improving model estimates and forecasts by assimilating observed water levels and flows.

6.1 Preparation of Mike Urban for EnKF

The prerequisite for using EnKF on a model is that the state variables of the model can be controlled from outside the model itself. Since 2013 a prototype of an API (Application Programming Interface) has made it possible to access the individual water level and flow variables of the hydrodynamic computational engine of Mike Urban and thereby opening up for the use of EnKF. In the current work this API was used to retrieve the relevant state variables from every model in the ensemble at every DA analysis time and put these into a state vector that is treated by the DA method. A prototype of a generic data assimilation framework from DHI was used as framework for the filtering. Once updated, the values in the DA vectors were inserted back into the models after a check for non-physical values that might have arisen during the analysis.

The API was furthermore used to replace the surface module of Mike Urban. This was done since in the current version of the software the hydrodynamic module only reads the surface runoff output at start-up, which means that it would be necessary to restart every model instance in the ensemble every time the states of the surface module has been altered. Another important prerequisite for any sequential data assimilation method is that the model has Markovian properties, which means that the state at the next time step only depends on the current state and the model forcing. The dominating sub-catchment surface runoff model in Danish DUDMs is the simple time-area model. This models the flow by multiplying the impervious surface area with the sum of rainfall within the last t_c minutes, where t_c is the time of concentration of the sub-catchment (typically values are in the range 7-60 minutes). If this is to be modelled as a Markov process with a one minute discretisation it requires that the model has a state variable for each of the previous t_c minutes of rainfall, which is a very large number of state variables for such a simple, and uncertain model. Therefore each of the time-area models was replaced with a two linear reservoir cascade model in the custom build surface module, with reservoir storages $s1$, and $s2$. The base flow from each catchment was furthermore routed through a single linear reservoir with reservoir storage sb and a long time constant. The state variable of this reservoir was added to the DA state vector instead of the base flow parameter itself, in order to prevent the base flow from drifting too far away from the initial value due to recursive updating.

In addition to the surface module states the water level variables from the hydrodynamic model were included in the state vector. The discharge variables, on the other hand, were not included since changes to the discharge variables only makes a very short term change to the model that is rapidly revoked by the large shear stress of the pipe system and does not affect the overall volume of water in the model. The DA state vectors used in the current work was defined as:

$$x = [s1_1, s2_1, sb_1, s1_2, s2_2, sb_2, \ldots., h_1, h_2, h_3, \ldots] \qquad (16)$$

where $s1_i$, $s2_i$ and sb_i are the states of the surface model governing the runoff from sub-catchment number i, and h_j denotes the water level at grid point number j.

6.2 Filter configuration

6.2.1 Forcing noise

The noise terms are essential for the EnKF and both forcing, process and observation noise needs to be specified. The dominating source of error during rain events comes from the model forcing, due to the large uncertainty of spatial rainfall estimates. It is assumed that any operational system using online DUDMs will have access to weather radar data and that forcing for the updated models will be based on ensembles of radar rainfall estimates. The creation of such representative ensembles is an ongoing field of research among radar meteorologist (e.g. Ciach et al., 2007; Germann et al., 2009; Villarini et al., 2009). For the current work the rainfall ensembles are made using a simple assumption about the error structure of radar rainfall estimates, which leads to rainfall perturbations being made by multiplying the observed rainfall with a factor that is randomly chosen at random intervals (see **Paper V** for details). A homogenous spatial distribution of the model forcing is assumed for all examples.

6.2.2 Process noise

In the current work the states of only the surface models are affected with noise, since these are regarded to be the most uncertain. They are furthermore the easiest to manipulate, since they consist of linear reservoir models of which the only physical restriction is that the state value should not be negative. The hydrodynamic module could be affected with noise without disturbing the mass balance or stability of the model by perturbing the parameters of the model, such as pipe roughness and minor losses in structures, but this has not been considered in the current work.

The errors on the surface model states are expected to be larger for larger state values, so the errors need to be state proportional. Furthermore, the ensemble mean should not change due to the perturbations, the perturbations should not result in unlimited error growth and it should be possible to parameterise the noise to reasonable values without extensive calibrations, since this will most likely not be feasible for large DUDMs. A suitable noise formulation for the surface reservoirs was created, inspired by the suggestion for making additive temporal correlated noise for the EnKF by Evensen (2003). Instead of focusing on the noise directly a perturbation method was developed by focusing on the impact of the noise on the ensemble spread and assuming that the temporal scale of the errors follows that of the linear reservoir (see appendix to **Paper V** for details):

$$x'_k = x_k + \sqrt{1-\beta^2}w_k em_k \tag{17}$$

where x and x' denotes the state variable before and after perturbation, β is a time dependent factor used to propagate the linear reservoir one step ahead, w is an element in a vector of spatially correlated white noise with zero mean and a variance of σ_w^2 and *em* is the ensemble mean. In this way temporally correlated perturbations of the ensemble are created with the same relative variance as w such that $\sigma_w = 0.1$ will result in a steady state ensemble spread of 10% if the inflow to the reservoir is constant and the state is not updated. This means that the process noise can be estimated from the modeller's assumption of what would be a reasonable uncertainty for the model with perfect rain input. An example of such perturbation of the states in a two reservoir cascade model can be seen in **Figure 1**.

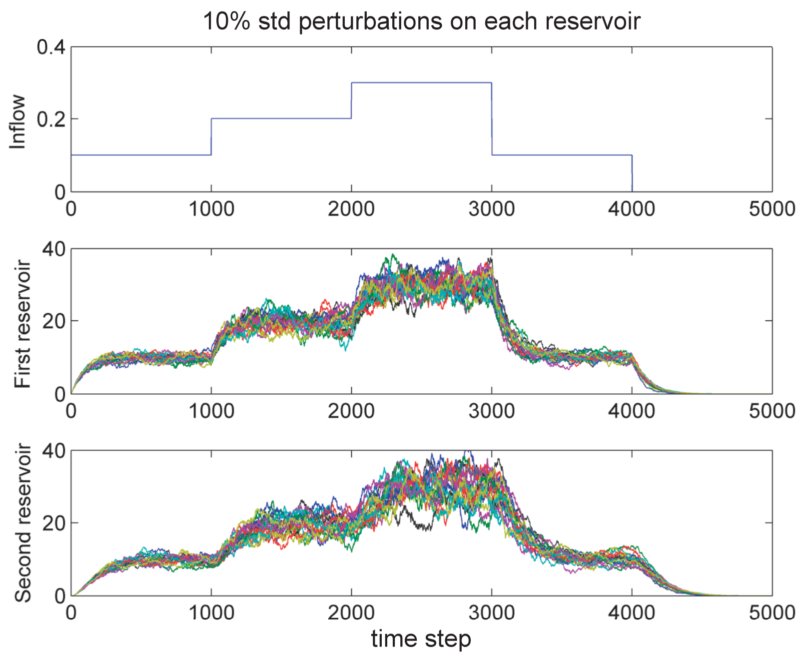

Figure 15: Dimensionless inflow to a two linear reservoir cascade model, and the state values in each of the two reservoirs for an ensemble with 20 members.

6.2.3 Filter tuning and observation errors

Filter tuning is a very time consuming process since it requires many filter runs with long periods of historical data. In the present work the only tuning performed was to increase the observation noise, which resulted in a dampening of the filter corrections and a slower reduction in the ensemble spread. Localisation and inflation were not considered. Note that some have successfully achieved their objectives without localisation and inflation. As an example, Clark et al. (2008) used EnKF to update distributed hydrological models from stream flow observations, without using these filter tuning methods.

Observation noise for flow and water level gauges was assumed to be additive and non-state proportional in the current work.

6.2.4 Ensemble size

In all tests a low number of ensemble members have been used (either 10 or 20 members), since this is expected to be the case for operational real time applications. The size of the ensemble is known to be a crucial parameter for EnKF performance and many reports on a certain threshold that should be superseded in order to obtain satisfactory filter performance. This threshold is, however, not independent from the other parameters of the filter, which for instance can be seen from the results presented in (Sakov and Oke, 2008) where the inflation factor used clearly is correlated with the minimum ensemble size required for obtaining a certain filter performance. Of all the parameters affecting the filter performance, the ensemble size is likely to be the one that is the most difficult to change in an operational system, since this entails a similar change in computational costs. The specification of the forcing, process and observation noise, on the other hand, can be more easily altered. In order to improve the performance with low ensemble sizes the main EnKF method used in the current work is the DEnKF.

6.3 Application examples

6.3.1 Adaption to changing hydraulic conditions: Gain, backwater effects and partial updating

One of the main reasons for exploring the use of EnKF to update the hydrodynamic states in DUDMs is the expectation that the method is able to adapt to changing hydraulic conditions in the system. This was tested using a simple Mike Urban model consisting of a single catchment and a 3.6 km pipe stretch with a throttle and an overflow structure close to the end (**Paper V**). Perfect model experiments were conducted using synthetic water level observations from the overflow structure while the effect of the updating was examined 2.5 km upstream. The results using EnKF with an ensemble size of 20 show that the filter is capable of reducing the spread of the initial ensemble considerably and get the ensemble mean very close to the true value for a large part of the event (see **Figure 16**). Note in the example without updating (**Figure 16**, upper left) how the upstream spread in the ensemble grows rapidly when the water level rises above 13 m. This is due to full running downstream pipes, which causes the water level to rise as a response to additional surface runoff, since it requires a large pressure gradient to raise the flow through the pipe additionally (cf. **Figure 3**). Notice also how most of the ensemble members at the weir (**Figure 16**, upper right) have almost the same value during the peak hour. This is caused by the fact that it is difficult for the water level to go much above the crest level, since this is associated with large overflow rates.

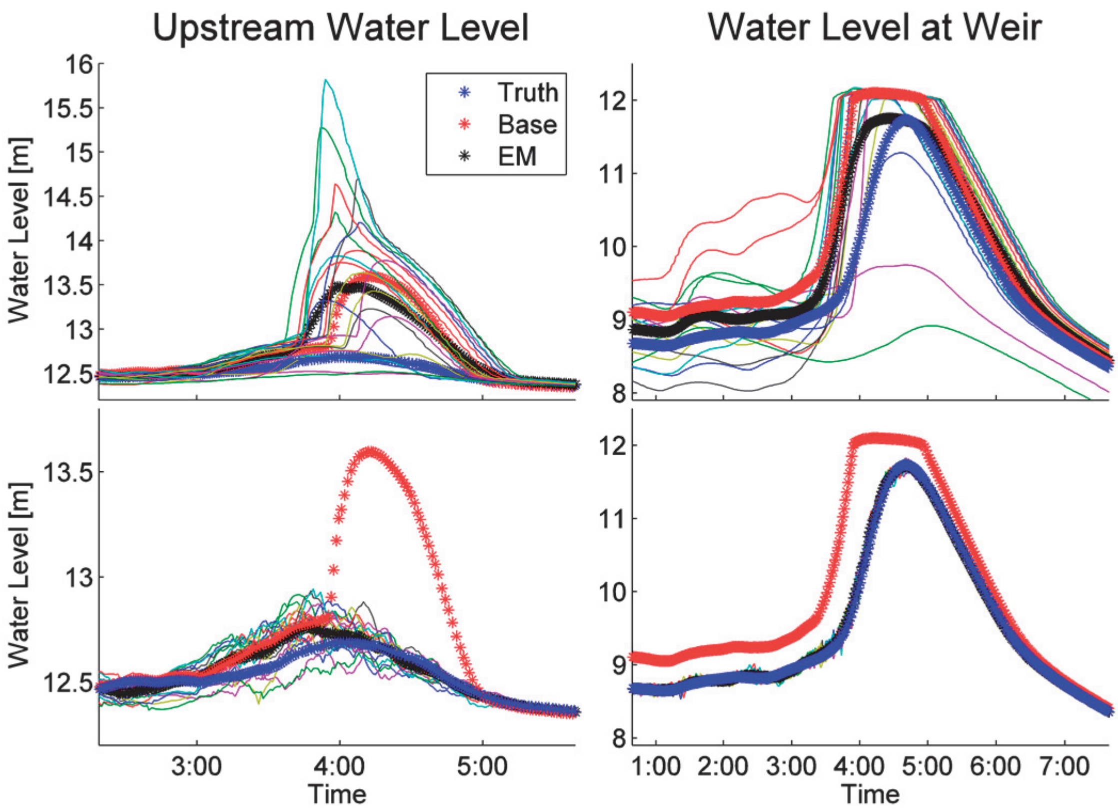

Figure 16: Ensemble of 20 models without updating (upper panel) and with EnKF updating (lower panel). The left panel shows the water level at the upstream validation point while the right panel shows the water level at the downstream weir. The dotted blue line shows the truth, the dotted red line the model as it would look without update and the black line the ensemble mean. (**Paper V**).

The corresponding gains computed for the same event clearly show how the filter adapts to the changing hydraulic conditions (see Figure 17). The large variations in the gains during this single event also indicate that a constant gain updating method is not suitable for updating the hydrodynamic states of a DUDM.

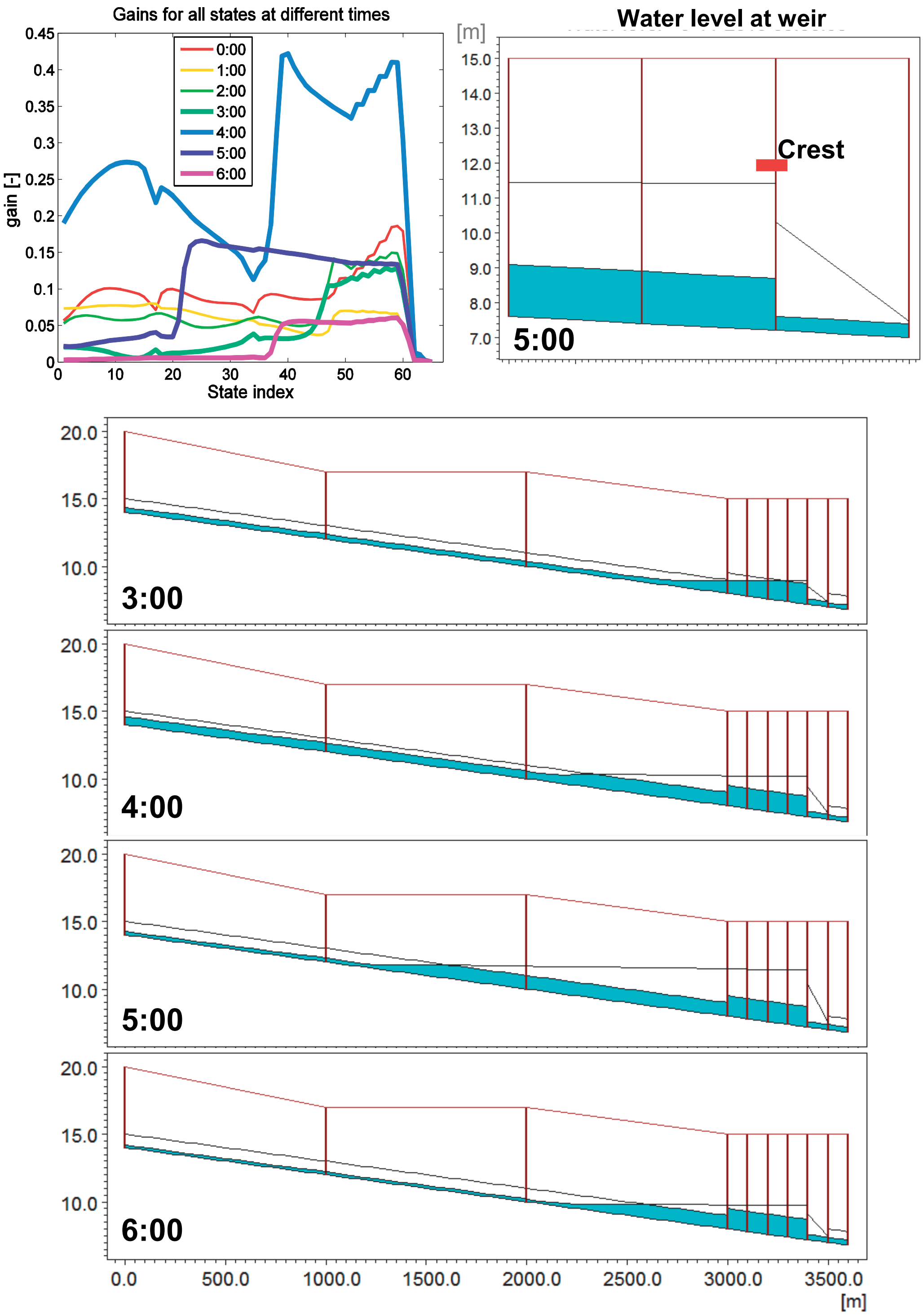

Figure 17: Changing gain and water levels in the test setup (**Paper V**). (top left) Gains for all water level grid points in the HD model for selected moments from the same event as in **Figure 16**. State index 59 is for the water level at the weir. (top right) Close-up at the section surrounding the overflow structure at 05:00 a 'clock. The thin black line indicates the water level/hydraulic grade line. (Lower four) Water levels in the system for four selected moments for which the gain can be seen in the upper left figure.

Using the same data as in the experiment above the partial updating method from **Paper VI** was tested with a gauge with a lower detection limit. The result of this can be seen in **Figure 18**. In the first period where there are no actual measurements the partial updating ensures that the ensemble members do not go much above the lower limit of the gauge (cf. **Figure 16**, top right) while the ensemble members are not restricted downwards by the updating. Once the first actual measurement arrives at approximately 03:10 the ensemble immediately concentrates around the observation. When performing the corresponding test where no partial updating had been used in the period up to the time where the water level reached the detection limit, several of the models in the ensemble would crash every time the updating started. This can be explained by the fact that the ensemble spread without partial updating becomes very large, see **Figure 16** (top right), so once the updating starts the observation is completely dominating and the water level at the observation point are, for some of the ensemble members, very violently forced almost two meters down. This produces gradients in the models that are much larger than what could be produced by the model itself, which causes it to become instable and crash. These very sudden changes are completely avoided by using the partial updating method, since this ensures a much smaller ensemble spread ones the actual observations are available.

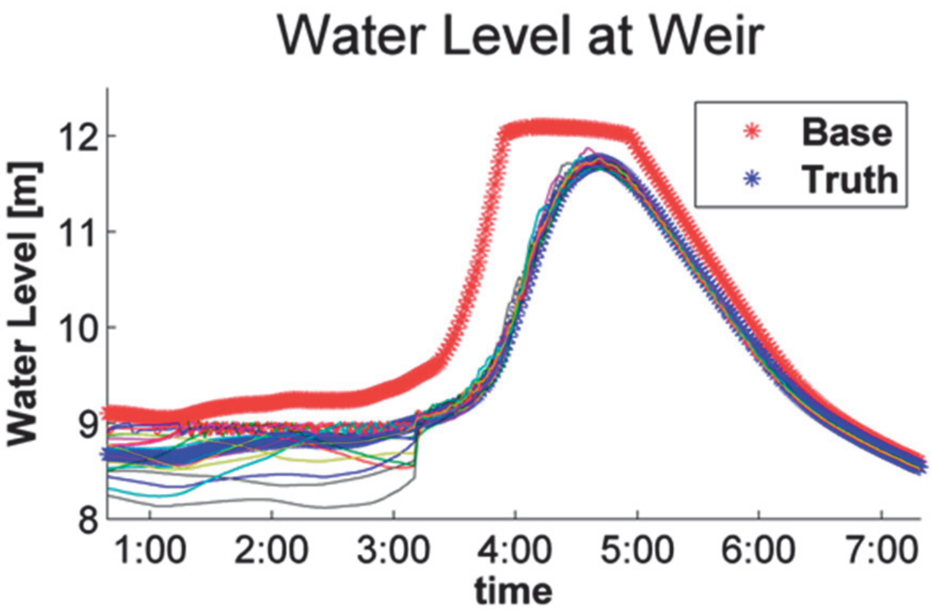

Figure 18: Using partial updating where a gauge in an overflow structure has a lower detection limit at 9 m. The dotted blue line show the truth and the red line the model as it would look without update. The ensemble mean has been omitted for figure clarity.

6.3.2 Using upstream water levels to improve downstream flow conditions

In another perfect model experiment using a small distributed model of a 107 ha catchment it was shown that far upstream water level observations can be used to improve downstream flow simulations significantly (**Paper V**). To test the filter's ability to work without the correct specification of the forcing error statistics two scenarios were tested: Scenario 1 where the rainfall estimates are uncertain but with known error statistics, and Scenario 2 where the only rainfall data available is whether it is raining or not. In Scenario 2 rainfall intensities of 2.5 μm/s and 0 μm/s, respectively, is assumed depending on rainfall or not. Both scenarios were tested using water level observations affected with both biased and unbiased Gaussian noise. When validating against the outflow from the catchment, see **Figure 19**, the filter showed to be most robust against observation errors if the forcing error statistics was specified correctly but the model results were still improved considerable if this was not the case.

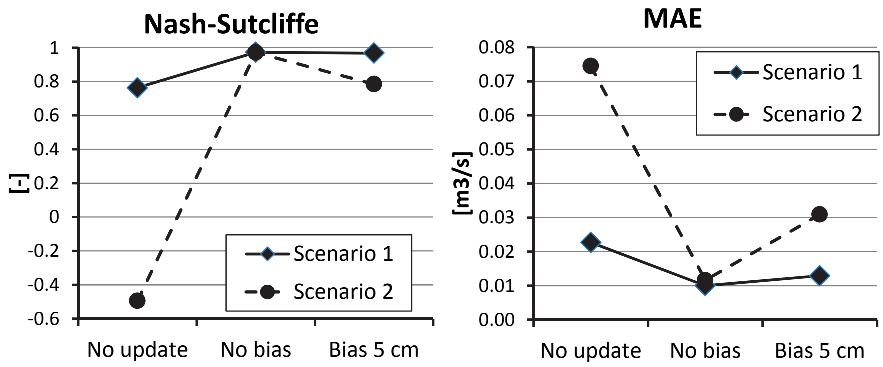

Figure 19: Mean Absolute Error and Nash-Sutcliffe efficiency index when the model is not updated (No update), when it is updated using water level observations with zero mean Gaussian observation noise (No bias), and when updated with water level observations with an unacknowledged bias of 5 cm (Bias 5 cm).

The test shows that even uncertain water level observations can be used to improve model performance and that upstream water level observations can compensate for poor rainfall data. It also shows, however, that good rainfall data makes the updated model less vulnerable to errors in the water level observations.

6.3.3 Improving forecasts for a real system

In order to test the method using real data and a full scale DUDM the EnKF was tested on the same model and data set that was used for the deterministic updating of slow-changing inflow in section 5.3 (**Paper V**). In the test the observed flow was used to update the water levels of a DUDM using the DEnKF. This was done by calculating the innovation for the filter from the difference between the observed flow and the modelled flow at the location of the observations. This means that the model itself is used as the measurement operator. The daily variations in the dry weather flow were not implemented in the surface runoff module, which explains why the simulated flow in **Figure 20** is much smoother then the observed flow in the periods with low flow. The RDII models were reduced to being only the two *Immediate Response* reservoirs and a surface storage, which is comparable to the reduced RDII case from section 5.3.

The same type of perturbation to the model forcing as used in the synthetic experiments above were applied to the raingauge data used, but with only half the variance to account for the expectation that raingauge data has a lower quantitative error than radar data. This error description is not in any way optimal, but as emphasized in Chapter 0 it is not possible to make a good representation of the spatial error distribution of rainfall when only sparse raingauge data is available. The observation error for the filter was roughly estimated to a value of 0.1 m^3/s. Note that this does not imply that the updated model will frequently be 0.1 m^3/s from the observed flow, due to the recursive nature of the filter. When looking at **Figure 20** (Left) it is seen that not even the 2 hour forecast is frequently this far from the observed value.

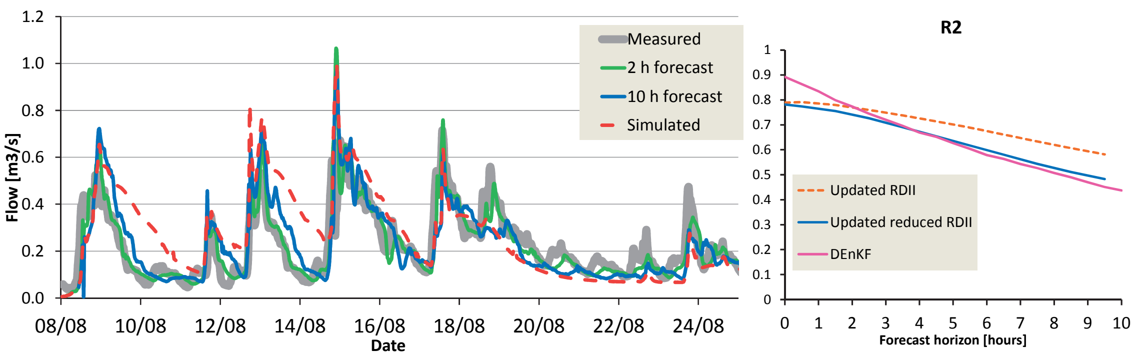

Figure 20: (Left) Observed discharge, simulated discharge without updating and the two and ten hour forecasts based on the DEnKF updated model. (Right) Nash-Sutcliffe efficiency index for forecasts when the model has been updated using the DEnKF plotted with the results from section 5.3 when only the RDII module states were updated using a deterministic method.

Figure 20 (Left) shows that forecasts based on the DEnKF updated models clearly performs better than a model simulation without update (dashed red line). The Nash-Sutcliffe efficiency index for up to ten hour forecasts based on the DEnKF updated model is compared with the results from section 5.3

(Deterministic updating; Slow changing inflow correction) for the reduced RDII case, see **Figure 20** (Right). The DEnKF updated model clearly performs best for the short forecasts with an R^2 close to 0.9 for the zero hour forecast. Note that this, in contrast to the case when updating the inflow only, is most likely to be due to updating of water levels in pipes close to the observation point, and therefore says very little about the DEnKF's ability to update the entire model. For the longer forecasts the results for the DEnKF based forecasts converge against the results for the inflow-corrected models. This indicates that the DEnKF is not better at updating the most upstream parts of the model than the more computationally efficient method from section 5.3.

6.4 Discussion

The examples shown in this chapter clearly show that the EnKF is suitable for updating DUDMs. Once the current noise formulation was in place the filter proved very stable in the sense that the models did not crash as long as the updating was performed continuously (as opposed to the case with limited range observations where the partial updating method was not used in section 6.3.1). Furthermore, the surface module noise made it close to impossible to make the filter diverge. The latter might be due to the fact that only a single observation point was used for the updating in each case, but also due to the nature of the system that implies that the filter is recharged with plenty of noise every time a new rain event starts. In long dry periods filter divergence might be a bigger problem, but these are usually not the periods of interest in urban drainage.

The use of very upstream water level observations to update a model could be an efficient way of correcting for the errors induced into the model by the rainfall estimates. Potentially, this kind of upstream water level observations could replace the role of raingauges to estimate the level of the rainfall as long as the spatial distribution of the rain is available through radar data. Since there is only direct feedback from a very small proportion of the model to the observed location, it will be easy to use ordinary distance dependent localisation schemes for upstream observations. It is not often seen that water level observation are placed very far upstream, since this kind of data has not been very useful so far. As demonstrated here, this changes with the introduction of EnKF for DUDMs.

The true benefit of using EnKF with DUDMs is when lots of different observations from multiple data sources can be synthesised with the filter. Time did not permit this to be investigated as part of this thesis.

7. Conclusions

This thesis develops and analyses several options for reducing uncertainty in online urban runoff modelling. Issues regarding the rainfall estimates used as model forcing as well as methods for updating the model states from system measurements using deterministic and ensemble based data assimilation methods have been investigated.

Rain data for online models
Once a runoff model is being updated dynamically in real time the requirements for model forcing change. Raingauge data is without question the most accurate for estimating rainfall in close proximity to the gauge, and in many cases this also applies to the catchment scale when looking at event volumes. Nonetheless, it has been shown that when the model is updated using observations from the system, the fact alone that it takes time for rain to travel the distance from a raingauge to a catchment is enough to drastically reduce the value of raingauge data compared to radar rainfall estimates. For e.g. 10 minute forecasts based on an updated model, time displacements of 5 and 10 minutes in the model forcing compares to radar data biases of 60% and 100%, respectively, in terms of reduced model forecast quality. This shows that the nature of radar data fits better conceptually to dynamically updated models, even when the quantitative accuracy is poor. Another important feature of radar rain estimates is the ability to describe the spatial distribution of rainfall, which is important when using distributed models.

Quantitative errors in radar rainfall estimates can be significant, so a method for reducing these errors was investigated. By merging high-resolution rainfall estimates from a weather radar with raingauge data, immediate radar rainfall estimates were improved to the extent that they performed similarly to a raingauge situated in the middle of a small 64 hectare urban catchment in terms of modelled overflow. This shows that radar data is indeed suitable as model forcing for online models as long as the radar data is frequently adjusted by raingauge data.

Deterministic updating of Distributed Urban Drainage Models (DUDMs):
For numerous reasons it can be convenient to use deterministic updating schemes to update a model. This is the case when the model is so computationally heavy that it is not realistic to use ensemble based methods, if the required input data for ensemble-based methods is unavailable, or if hydrodynamic states are simply unavailable for external control. In this case an existing option is to update water

levels at selected individual points in the model. If this is done in basins of substantial volume, this simple update method can lead to notable intermediate forecast improvements.

A new method developed during this PhD project focuses on deterministically updating inflow into the hydrodynamic module in cases where a substantial part of the inflow is governed by timescales greater than the hydraulic response of the pipe system, as often is the case with infiltration inflow. The key element in this update procedure is to create a linearised model of the hydraulic model's response, which is then used to calculate a dampened feedback of the model error to the surface runoff model states, in order to produce a fast update without producing system instability. The method is shown to be capable of increasing the quality of long-range forecasts significantly, without any notable increase in computational cost.

The main limitation of the deterministic methods is that they do not estimate the model uncertainty without which it is not possible to determine how much the observation should be trusted compared to the model. This is a major drawback in regards to updating urban drainage models since the uncertainty of these can change a lot over time.

Ensemble-based data assimilation methods for DUDMs

When it is feasible to run multiple instances of a model in parallel, and the model states can be controlled, ensemble-based updating methods can be used. In order to use ensemble-based updating on a DUDM it is necessary to create an ensemble representation of the rain which takes the spatial variability of the rain into account. Due to the large spatial variability of rain, the usage of only a limited number of raingauges results in an almost unlimited number of degrees of freedom, thus making it impossible to create a reasonable ensemble representation. Therefore, the use of radar data is seen as a prerequisite for the effective ensemble updating of DUDMs. Assuming radar data that perfectly describes the spatial variability of rain, and assuming a perfect hydrodynamic model, it was shown that the Ensemble Kalman Filter (EnKF) is suitable for updating DUDMs. The assumption will, of course, not hold completely in real-life applications where the quality of the model and rainfall data will determine the case-specific need for filter tuning measures such as localisation, inflation and dampening. These issues have only been discussed briefly in the current work and are left for future investigations. In an experiment with measured flow data it was shown that even without radar data and without the use of inflation and localisation, the EnKF could improve flow forecasts significantly. To what extent the updating improved the upstream state estimates is not known due to the lack of upstream observations.

Many data sources within urban drainage systems are not continuous measurements with Gaussian observation uncertainty, but rather irregular observations that are discontinuous in time because the observed quantity falls outside the observed range of a gauge. Sometimes the data is even Boolean in nature, such as pumps running (or not) or water flowing over a weir (or not). A new method was developed that allows the EnKF to utilise the information present in these kinds of observations. This method can significantly increase the amount of data available for data assimilation in urban runoff modelling, but it also has the potential to be used within other fields of research.

This thesis contributes some important stepping stones towards the online use of physically based, distributed urban drainage models. Provided that a good model exists for an urban area with weather radar data coverage, the methods are now available for synthesising most of the data from the system in an online model.

8. Potentials for further research

In many ways research concerning data assimilation for urban drainage models has only just begun. In all the examples with ensemble based data assimilation in the current work only a single observation was used for updating the model for each setup. The next natural step is to test the methods with numerous observations spread out over the catchment. Such an experiment is likely to lead to the need for implementing process noise in the hydrodynamic part of the model. How this can be done in a reasonable way is still an unanswered question. An alluring possibility would be to include the roughness of the pipes in the DA state vector and then applying spatially correlated noise to this parameter. This will have the desired side effect that it could be possible to assess the level of sedimentation in the pipes and thereby the need for maintenance in parts of the system.

The filter tuning methods, inflation and localisation, have only been touched upon briefly in the current work. In operational systems some sort of filter tuning is likely to be required and therefore this subject needs to be addressed. As mentioned in this thesis it is difficult to think of a suitable measure of distance for localisation schemes for distributed urban drainage models, and therefore this subject alone could prove suitable for extensive further research.

In the current study only the mean of the probability density function (pdf) provided by the EnKF ensemble is evaluated. Future work could include the evaluation of the entire pdf for the current state estimate as well as for the forecasts. The latter involves forecasting with the entire ensemble, which of course is a much more computationally demanding process than just forecasting with the ensemble mean as it was done in the current work. Nonetheless, the pdf of forecasts is of such big importance for model predictive control purposes, that the increased computational cost is likely to be an expense worth paying in an operational setting.

9. References

Anderson, J.L., 2007. An adaptive covariance inflation error correction algorithm for ensemble filters. *Tellus A* **59**, 210–224.

Anderson, J.L., Anderson, S.L., 1999. A Monte Carlo implementation of the nonlinear filtering problem to produce ensemble assimilations and forecasts. *Monthly Weather Review* **127**, 2741–2758.

Arulampalam, M.S., Maskell, S., Gordon, N., Clapp, T., Sanjeev Arulampalam, M., Maskell, S., Gordon, N., Clapp, T., Arulampalam, M.S., 2002. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on Signal Processing* **50**, 174–188.

Benedetti, L., Langeveld, J., Comeau, A., Corominas, L., Daigger, G., Martin, C., Mikkelsen, P.S., Vezzaro, L., Weijers, S., Vanrolleghem, P.A., 2013. Modelling and monitoring of integrated urban wastewater systems: review on status and perspectives. *Water Science & Technology* **68**(6), 1203–1215.

Berne, A., Delrieu, G., Creutin, J.-D., Obled, C., 2004. Temporal and spatial resolution of rainfall measurements required for urban hydrology. *Journal of Hydrology* **299**, 166–179.

Bertrand-Krajewski, J.L., Bardin, J.P., Mourad, M., Béranger, Y., 2003. Accounting for sensor calibration, data validation, measurement and sampling uncertainties in monitoring urban drainage systems. *Water Science and Technology* **47**, 95–102.

Borup, M., Grum, M., Linde, J.J., Mikkelsen, P.S., 2009. Application of high resolution x-band radar data for urban runoff modelling: constant vs. dynamic calibration, in: Rainfall in the Urban Context: Forecasting, Risk and Climate Change. 8th International Workshop on Precipitation in Urban areas,10-13 December, 2009, St. Moritz, Switzerland. *Eidgenüssische Technische Hochschule Zürich, Laboratorium für Lebensmittel-Verfahrenstechnik*, 27–31.

Breinholt, A., 2012. Uncertainty in prediction and simulation of flow in sewer systems. PhD Thesis, *DTU Environment*.

Breinholt, A., Thordarson, F.Ö., Møller, J.K., Grum, M., Mikkelsen, P.S., Madsen, H., 2011. Grey-box modelling of flow in sewer systems with state-dependent diffusion. *Environmetrics* **22**, 946–961.

Brocca, L., Melone, F., Moramarco, T., Wagner, W., Naeimi, V., Bartalis, Z., Hasenauer, S., 2010. Improving runoff prediction through the assimilation of the ASCAT soil moisture product. *Hydrology and Earth System Sciences* **14**, 1881–1893.

Brødbæk, D., 2013. Improving Data for Real-Time Control of Urban Sewer Systems. Master Thesis, *Aalborg University.*

Burgers, G., Jan van Leeuwen, P., Evensen, G., 1998. Analysis Scheme in the Ensemble Kalman Filter. *Monthly Weather Review* **126**, 1719–1724.

Butler, D., Davies, J., 2004. *Urban drainage. Taylor & Francis*.

Campisano, A., Cabot Ple, J., Muschalla, D., Pleau, M., Vanrolleghem, P. a. A., 2013. Potential and limitations of modern equipment for real time control of urban wastewater systems. *Urban Water Journal* **10**, 300–311.

Ciach, G.J., Krajewski, W.F., Villarini, G., 2007. Product-Error-Driven Uncertainty Model for Probabilistic Quantitative Precipitation Estimation with NEXRAD Data. *Journal of Hydrometeorology* **8**, 1325–1347.

Clark, M.P., Rupp, D.E., Woods, R. a, Zheng, X., Ibbitt, R.P., Slater, A.G., Schmidt, J., Uddstrom, M.J., 2008. Hydrological data assimilation with the ensemble Kalman filter: Use of streamflow observations to update states in a distributed hydrological model. *Advances in Water Resources* **31**, 1309–1324.

Cooper, M., Fernando, D.A.K., 2009. The effect of the raingauge distribution on stormwater models. In *Proceeding of the 18th World IMACS/MODSIM Congress*, Cairns, Australia, 13-17 July 2009, 3500–3506.

Delft, G. Van, Serafy, G. El, Heemink, A., 2009. The ensemble particle filter (EnPF) in rainfall-runoff models. *Stochastic Environmental Research and Risk Assessment* **23**, 1203–1211.

DHI, 2009. MOUSE RDII Reference Manual.

El Serafy, G.Y.H., Mynett, A.E., 2008. Improving the operational forecasting system of the stratified flow in Osaka Bay using an ensemble Kalman filter--based steady state Kalman filter. *Water Resources Research* **44**, 1–19.

Erdal, D., Neuweiler, I., Wollschläger, U., 2014. Using a bias aware EnKF to account for unresolved structure in an unsaturated zone model. *Water Resources Research* **50**, 1–16.

Evensen, G., 1994. Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. *Journal of Geophysical Research* **99**, 10143–10162.

Evensen, G., 2003. The Ensemble Kalman Filter: theoretical formulation and practical implementation. *Ocean Dynamics* **53**, 343–367.

Evensen, G., 2009. Data Assimilation. Springer Berlin Heidelberg, Berlin, Heidelberg.

Fach, S., Sitzenfrei, R., Rauch, W., 2009. Determining the spill flow discharge of combined sewer overflows using rating curves based on computational fluid dynamics instead of the standard weir equation. *Water Science and Technology* **60**, 3035-3043.

FRI, 2008. State of the nation 2008. *Forening af Rådgivende Ingeniører – FRI Publication*.

Furrer, R., Bengtsson, T., 2007. Estimation of high-dimensional prior and posterior covariance matrices in Kalman filter variants. *Journal of Multivariate Analysis* **98**, 227–255.

Germann, U., Berenguer, M., Sempere-torres, D., Zappa, M., 2009. REAL – Ensemble radar precipitation estimation for hydrology in a mountainous region. *Quarterly Journal of the Royal meteorological Society* **135**, 445–456.

Gerstner, E.-M., Heinemann, G., 2008. Real-time areal precipitation determination from radar by means of statistical objective analysis. *Journal of Hydrology* **352**, 296–308.

Gordon, N.J., Salmond, D.J., Smith, A.F.M., Gordon, 1993. Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE Proceedings F* **140**,107–113.

Goudenhoofdt, E., Delobbe, L., 2009. Evaluation of radar-gauge merging methods for quantitative precipitation estimates. *Hydrology and Earth System Sciences* **13**, 195-203.

Hamill, T., Whitaker, J., Snyder, C., 2001. Distance-dependent filtering of background error covariance estimates in an ensemble Kalman filter. *Monthly Weather Review* **129**, 2776–2790.

Heemink, a. W., Kloosterhuis, H., 1990. Data assimilation for non-linear tidal models. *International Journal for Numerical Methods in Fluids* **11**, 1097–1112.

Hendricks Franssen, H.J., Kinzelbach, W., 2008. Real-time groundwater flow modeling with the Ensemble Kalman Filter: Joint estimation of states and parameters and the filter inbreeding problem. *Water Resources Research* **44**, 1–21.

Houtekamer, P., Mitchell, H., 2001. A sequential ensemble Kalman filter for atmospheric data assimilation. *Monthly Weather Review* **129**, 123–137.

Houtekamer, P.L.P., Mitchell, H.L.H., 1998. Data assimilation using an ensemble Kalman filter technique. *Monthly Weather Review* **126**, 796–811.

Isel, S., Dufresne, M., Bardiaux, J.B., Fischer, M., Vazquez, J., 2013. Computational fluid dynamics based assessment of discharge-water depth relationships for combined sewer overflows. *Urban Water Journal,* (ahead-of-print), 1–10.

Jazwinski, A.H., 1970. Stochastic processes and filtering theory. *Academic Press*.

Judd, K., Smith, L. a., 2004. Indistinguishable states II The imperfect model scenario. *Physica D* **196**, 224–242.

Kalman, R.E., 1960. A new approach to linear filtering and prediction problems. *Journal of basic Engineering* **82**, 35–45.

Kepert, J., 2009. Covariance localisation and balance in an ensemble Kalman filter. *Quarterly Journal of the Royal Meteorological Society* **135**, 1157–1176.

Lanza, L.G., Stagi, L., 2009. High resolution performance of catching type raingauges from the laboratory phase of the WMO Field Intercomparison of Rain Intensity Gauges. *Atmospheric Research* **94**, 555–563.

Li, H., Kalnay, E., Miyoshi, T., 2009. Simultaneous estimation of covariance inflation and observation errors within an ensemble Kalman filter. *Quarterly Journal of the Royal Meteorological Society* **135**, 523–533.

Liu, Y., Gupta, H. V., 2007. Uncertainty in hydrologic modeling: Toward an integrated data assimilation framework. *Water Resources Research* **43**, 1–18.

Löwe, R., Mikkelsen, P.S., Madsen, H., 2013a. Stochastic rainfall-runoff forecasting: parameter estimation, multi-step prediction, and evaluation of overflow risk. *Stochastic Environmental Research and Risk Assessment **28***, 505-516.

Löwe, R., Mikkelsen, P.S., Rasmussen, M.R., Madsen, H., 2013b. State-space adjustment of radar rainfall and skill score evaluation of stochastic volume forecasts in urban drainage systems. *Water science and technology* **68**, 584–90.

Löwe, R., Thorndahl, S., Steen, P., Rasmussen, M.R.,. Probabilistic online runoff forecasting for urban catchments using inputs from raingauges as well as statically and dynamically adjusted weather radar. *Journal of Hydrology* Submitted.

Madsen, H., Skotner, C., 2005. Adaptive state updating in real-time river flow forecasting—a combined filtering and error forecasting procedure. *Journal of Hydrology* **308**, 302–312.

Marshall, R.J., 1980. The estimation and distribution of storm movement and storm structure, using a correlation analysis technique and rain-gauge data. *Journal of Hydrology* **48**, 19–39.

McMillan, H., Krueger, T., Freer, J., 2012. Benchmarking observational uncertainties for hydrology: rainfall, river discharge and water quality. *Hydrological Processes* **26**, 4078–4111.

Mitchell, H.L., Houtekamer, P.L., 2009. Ensemble Kalman filter configurations and their performance with the logistic map. *Monthly Weather Review* **137**, 4325–4343.

Mollerup, A. (HOFOR), 2013. Personal communication.

Neff, E.L., 1977. How much rain does a rain gage gage? *Journal of Hydrology* **35**, 213–220.

Nielsen, J.E., Beven, K., Thorndahl, S., Rasmussen, M.R., 2014. GLUE based marine X-band weather radar data calibration and uncertainty estimation. *Urban Water Journal,* (ahead-of-print),1-12. DOI: 10.1080/1573062X.2013.871044

Niemczynowicz, J., 1987. Storm tracking using raingauge data. *Journal of Hydrology* **93**, 135–152.

Oke, P.R., Sakov, P., Corney, S.P., 2007. Impacts of localisation in the EnKF and EnOI: experiments with a small model. *Ocean Dynamics* **57**, 32–45.

Ott, E., Hunt, B.R., Szunyogh, I., Zimin, A. V, Kostelich, E.J., Corazza, M., Kalnay, E., Patil, D.J., Yorke, J.A., 2004. A local ensemble Kalman filter for atmospheric data assimilation. *Tellus A* **56**, 415–428.

Plósz, B.G., Reid, M.J., Borup, M., Langford, K.H., Thomas, K. V, 2013. Biotransformation kinetics and sorption of cocaine and its metabolites and the factors influencing their estimation in wastewater. *Water research* 4**7,** 2129-2140.

Rasmussen, M.R., Thorndahl, S., Grum, M., Neve, S., Borup, M., 2008. Vejrradarbaseret styring af spildevandsanlæg. *Miljøministeriet. By- og Landskabsstyrelsen*.

Rinehart, R.E., 2010. Radar for meteorologists – Fifth Edition. Department of Atmospheric Sciences, Center for Aerospace Sciences, *University of North Dakota*.

Sakov, P., Oke, P.R., 2008. A deterministic formulation of the ensemble Kalman filter: an alternative to ensemble square root filters. *Tellus A* **60**, 361–371.

Seo, B.-C., Krajewski, W.F., 2010. Scale Dependence of Radar Rainfall Uncertainty: Initial Evaluation of NEXRAD's New Super-Resolution Data for Hydrologic Applications. *Journal of Hydrometeorology* **11**, 1191–1198.

Sevruk, B., 1996. Adjustment of tipping-bucket precipitation gauge measurements. *Atmospheric Research* **42**, 237–246.

Sun, A.Y., Morris, A., Mohanty, S., 2009. Comparison of deterministic ensemble Kalman filters for assimilating hydrogeological data. *Advances in Water Resources* **32**, 280–292.

Te Chow, V., Maidment, D.R., Mays, L.W., 1988. Applied hydrology. *Tata McGraw-Hill Education*.

Thordarson, F.Ö., Breinholt, A., Møller, J.K., Mikkelsen, P.S., Grum, M., Madsen, H., 2012. Evaluation of probabilistic flow predictions in sewer systems using grey box models and a skill score criterion. *Stochastic Environmental Research and Risk Assessment* **26**, 1151–1162.

Thorndahl, S., Nielsen, J.E., Rasmussen, M.R., 2014. Bias adjustment and advection interpolation of long-term high resolution radar rainfall series. *Journal of Hydrology* **508**, 214–226.

Thorndahl, S., Poulsen, T.S., Bøvith, T., Borup, M., Ahm, M., Nielsen, J.E., Grum, M., Rasmussen, M.R., Gill, R., Mikkelsen, P.S., 2013. Comparison of short-term rainfall forecasts for model-based flow prediction in urban drainage systems. *Water Science and Technology* **68**, 472–478.

Tippett, M.K.M., Anderson, J.L.J., Bishop, C.H., Hamill, T.M., Whitaker, J.S., 2003. Ensemble square root filters*. *Monthly Weather Review* **131**, 1485–1490.

Villarini, G., Krajewski, W.F., Ciach, G.J., Zimmerman, D.L., 2009. Product-error-driven generator of probable rainfall conditioned on WSR-88D precipitation estimates. *Water Resources Research* **45**, 1–11.

10. Papers

I. **Borup, M.,** Grum, M., Mikkelsen, P.S., 2013. Comparing the impact of time displaced and biased precipitation estimates for online updated urban runoff models. *Water Science and Technology* **68**(1), 109–116.

II. **Borup, M.**, Grum, M., Linde, J.J., Mikkelsen, P.S., 2009. Application of high resolution x-band radar data for urban runoff modelling: constant vs. dynamic calibration, in: *Proceedings of 8th International Workshop on Precipitation in Urban* Areas, 10-13 December, 2009, St. Moritz, Switzerland. 27–31.

III. **Borup, M.**, Grum, M., Mikkelsen, P.S., 2011. Real time adjustment of slow changing flow components in distributed urban runoff models, in: *Proceedings of the 12th International Conference on Urban Drainage*. Porto Alegre/Brazil, 11-16 September 2011. Full paper PAP005261. 8 p.

IV. Hansen, L.S., **Borup, M.**, Møller, A., Mikkelsen, P.S., 2011. Flow Forecasting using Deterministic Updating of Water Levels in Distributed Hydrodynamic Urban Drainage Models. (Manuscript).

V. **Borup, M.**, Grum, M., Madsen, H., Mikkelsen, P.S., Updating distributed, physically-based urban drainage models using the Ensemble Kalman Filter. (Manuscript).

VI. **Borup, M.**, Grum, M., Madsen, H., Mikkelsen, P.S., A Partial Ensemble Kalman Filtering approach to enable use of range limited observations. (In revision).

In this online version of the thesis, the papers are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from:

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The department dates back to 1865, when Ludvig August Colding, the founder of the department, gave the first lecture on sanitary engineering as response to the cholera epidemics in Copenhagen in the late 1800s.

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